Advancements in On-Board Processing of Synthetic Aperture Radar (SAR) Data: Enhancing Efficiency and Real-time Capabilities

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***Abstract*—Satellite-borne Synthetic Aperture Radar (SAR) technology has revolutionized remote sensing applications by providing high-resolution and all-weather imaging capabilities. With the increasing availability of SAR data, the need for efficient data processing has become crucial. On-board processing has emerged as a promising solution to address the challenges associated with limited downlink capacity and final data products latency. Performing data processing and compression directly on the airborne platform reduces the raw data transmitted to ground stations, which offers several key benefits. Firstly, it significantly reduces the data volume to be downlinked, optimizing the usage of limited bandwidth and minimizing transmission delays. Secondly, on-board processing enables faster access to processed data products, allowing for quicker decision-making and timely response to dynamic events, enhancing the real-time capabilities of the system that are particularly valuable in time-critical applications. This article discusses various on-board processing techniques employed in SAR systems and explores their challenges, like computational constraints, architectural impacts, power consumption, and algorithm optimization. Furthermore, it examines the potential future developments in on-board processing, such as the integration of artificial intelligence and machine learning techniques to enhance data analysis and decision-making capabilities. The advancements in on-board processing have the potential to revolutionize the way SAR missions are conducted. By leveraging these techniques, SAR systems can achieve improved operational efficiency, reduced data latency, and enhanced real-time capabilities. This article emphasizes the significance of on-board processing in meeting the growing demands of SAR applications and underscores its role in advancing remote sensing capabilities for various sectors, including environmental monitoring, disaster response, and surveillance.**

***Index Terms*—Synthetic Aperture Radar (SAR), on-board processing, efficiency, real-time capabilities, data compression, image formation, remote sensing**

I. Introduction

SAR technology has revolutionized the way we perceive and understand the Earth's surface from space. Originating in the mid-20th century, SAR provides high-resolution, all-weather, and day-and-night imaging capabilities, making it a valuable tool for diverse applications, ranging from environmental monitoring to defense reconnaissance [1]. SAR systems, however, are data-intensive, often generating vast amounts of information requiring considerable processing power. Traditionally, the heavy computational demands have necessitated that space-generated SAR data be downlinked to ground stations for post-processing, introducing inherent delays in information availability and posing challenges for real-time or near-real-time applications [2]. As a result, the necessity for SAR on-board processing has become a topic of significant interest and importance in the field of remote sensing and spaceborne technology.

As satellite technologies continue to advance and data rates steadily increase, the quantities of SAR data produced have reached staggering levels. For example, the Sentinel Data Access system for the year 2022 was supporting over 638,000 users, who were downloading an average of 234 TiB of data packages per day. By the end of December 2022, a total data volume of 403 PiB data packages had been downloaded since the data first started being available. Furthermore, in 2022 alone, the user-level data published amounted to 13,766,370, with a total data volume of 6.64 PiB, surpassing the entire ESA collection of Earth Observation (EO) data from before Copernicus was launched. By the end of 2013, this collection was only 5.6 PiB [3]. Traditionally, the standard procedure involved the transmission of raw data to ground stations for subsequent processing; however, this conventional approach poses inherent challenges. The temporal lag between data acquisition and availability for analysis (and furthermore, the availability of its derived insight), the demand for downlink bandwidth, and the storage constraints aboard the satellite are factors contributing to the inefficiency of raw data transmission [4]. On-board processing of SAR data addresses these challenges by preemptively reducing data volume before transmission, facilitating a more judicious utilization of satellite resources and expediting data availability on the ground.

The significance of on-board processing cannot be overstated, particularly in applications necessitating real-time data, such as disaster monitoring, defense operations, or rapid environmental change detection.

It is crucial to emphasize that the term "downloaded" does not inherently imply utilization by commercial and private end-users. The protracted subsequent processing and special-

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ized expertise required to extract meaningful insights from EO images curtails widespread utilization among end-users who may not be closely acquainted with the intricacies of the EO domain. In this context, Artificial Intelligence (AI) emerges as a pivotal component in delivering timely insights and information to end-users with diverse backgrounds and requirements.

In the 1990s, with the rise of advanced digital electronics, the first rudimentary on-board SAR processing attempts were initiated. These sought to mitigate the data deluge by introducing basic compression and some elementary image formation techniques before downlinking [5]. By the 2000s, advancements in Field-Programmable Gate Arrays (FPGAs) and Application-Specific Integrated Circuits (ASICs) opened doors to more intricate on-board SAR processing methodologies, enabling more than just compression but also rudimentary image analytics [6]. The recent decade, however, has witnessed a paradigm shift. With the advent and success of artificial intelligence (AI) and machine learning (ML) in image analysis tasks, there is a growing emphasis on not only processing SAR data on-board but also interpreting it. Emerging hardware technologies, such as advanced FPGAs and Graphic Processing Units (GPUs), paired with efficient, lightweight deep learning (DL) models, are redefining the boundaries of on-board SAR processing. Techniques like real-time anomaly detection and target classification, once believed to be feasible only on powerful ground-based systems, are now being implemented directly on satellite platforms [7].

Nevertheless, the question remains: why the persistent push for on-board processing when we have ever-increasing downlink speeds and very efficient ground stations? The answers are multifaceted. Firstly, the real-time requirements of many applications, ranging from defense to disaster response, demand immediate information and actionable data availability directly to the end user. It is essential to explicitly specify the identity of the end-user, as space economy studies often encounter confusion in this regard. AI enhances the potential to target not only the conventional end-user from the institutional/public sector or academia and research entities but also the private/commercial sector, i.e., companies utilizing services and applications from space assets to enhance internal processes and provide superior solutions to their customers [8].

Secondly, the sheer volume of Synthetic Aperture Radar (SAR) data, especially from modern high-resolution systems, possesses the capability to overwhelm and present challenges in storage, downlink, and management, thereby escalating ground infrastructure complexity and costs. On-board processing offers a solution by enabling the transmission of only pertinent, processed information or imagery, thereby conserving both time and bandwidth. Furthermore, in an era where satellite constellations and swarms are becoming more prevalent, on-board processing can facilitate inter-satellite communications, thereby further optimizing data management and transmission [9].

Third, the geographical distribution of satellite ground stations can be a challenge for delivering low-latency EO products. Ground stations are concentrated in certain regions, often developed nations, and geopolitical issues may contribute to accessibility. This leaves gaps in coverage, especially over oceans and remote areas. When a satellite carrying EO data passes over a gap, the data can't be downloaded in real-time. Furthermore, ground stations are typically built based on factors like infrastructure and operational costs. This doesn't always align perfectly with ideal locations for maximizing satellite contact. For low-latency applications, consistent contact with the satellite is crucial since most EO satellites are in Low Earth Orbit (LEO), meaning they complete a revolution around Earth quite quickly. This necessitates frequent contact with ground stations to capture all the data. Sparse ground station networks can lead to missed data packets during these short windows.

In contrast, geostationary SAR satellites, positioned at a much higher altitude in geostationary orbit, remain fixed over a specific point on the Earth's surface. This unique positioning allows them to continuously monitor a particular area without the need for frequent passes over ground stations [10]. Unlike LEO satellites, a geostationary SAR satellite can significantly reduce the dependency on ground station geographic distribution. However, while geostationary SAR technology presents a potential solution to coverage and latency issues, it also presents challenges, like signal attenuation (due to the higher orbit), requiring more powerful transmitters and larger antennas on the satellites and the ground stations. Moreover, the fixed coverage area might limit the flexibility in observing global phenomena that require data from multiple parts of the Earth. Despite these considerations, the integration of geostationary SAR technology could play a significant role in addressing the geographical and latency challenges associated with the current reliance on LEO satellites and ground station networks [11].

The remainder of the paper is structured as follows: Section II details the techniques and challenges involved in on-board processing for SAR systems, alongside improvements in the relevant hardware involved. Section III delves into the real-time processing abilities of spaceborne SAR systems and proposes methods to enhance these capabilities. The application of AI in processing SAR data is explored in Section IV, focusing on data availability and potential AI applications. Section V introduces and examines the information-driven approach to SAR processing, contrasting it with the traditional image-driven method. The paper concludes with Section VI, where conclusions are presented.

II. ON-BOARD PROCESSING IN SAR SYSTEMS

The capabilities of SAR in EO are changing how we perceive and understand our planet. As SAR systems generate a vast amount of data, the challenge of processing, storing, and transmitting this information efficiently has become paramount. Traditionally, SAR data processing has been performed on the ground stations, following data downlink from the satellite. However, the need for faster data access and the increasing demand for real-time applications, combined with limitations in downlink bandwidth and storage, are shifting the focus towards on-board data processing. This offers several advantages, such as latency reduction, faster data availability for time-critical applications, bandwidth efficiency, data volume reduction, and operational flexibility, allowing for adaptive mission planning based on real-time analysis.

The data rate on-board depends on several key parameters of the system: the pulse repetition frequency (PRF), the sampling rate of each received pulse, the quantization level, the radar bandwidth, the swath width, the number of channels of the SAR system, and the spatial resolution. For example, Sentinel-1 SAR operates in C-band and has a payload input data rate of 2x640 Mbps for multi-polarization acquisition or 1x1280 Mbps for single-polarization acquisition, with a storage capacity of only 1410 Gbit [12]. ALOS-2 (Advanced Land Observing Satellite-2), operating in L-band, reaches a data rate of 800Mbps in its highest resolution [13]. The SAOCOM (SAtélite Argentino de Observación COn Microondas) has an on-board mass memory capacity of 256 Gbit, with Telemetry, Tracking, and Control (TT&C) communications via the S-band. The SAR data is transmitted to the ground using the X-band, with a data downlink rate of 310 Mbps [14].

Storage capacity and downlink availability pose limitations on the acquisition duty cycle of the sensor, especially for small platforms with limited downlink bandwidth.
On-board processing helps to reduce the data quantities by compressing raw SAR data or executing application-specific processing prior to the data downlink [15]. This not only optimizes the satellite resources but also speeds up the delivery of useful information to end-users. Downlink data rate has been constantly improving to keep up with the data generated by the sensors, with systems starting to employ Ka-band downlink with over 1 Gbps downlink [16], and looking towards the adoption of optical downlink [17]. The current bottleneck is the increasing azimuth resolution and swath of the satellite, which increases the amount of raw data generated and poses an important challenge for on-board processing. The sensor data rate is dependent on the PRF (which correlates to the azimuth resolution), the swath or range line length, and the actual resolution of the analog to digital converters employed. Taking the Sentinel-1 example mentioned before in stripmap mode, with a swath of 80 km and resolution of 5 m, up to 20000 range lines are required. With a PRF of around 1600 Hz, the maximum payload input data rate of 2x640 Mbps is obtained. This assumes a maximum raw analog to digital conversion resolution of 10 bits, which can be reduced with different compression methods down to 3 bits in most operational scenarios [18].
New missions with similar azimuth resolution target much larger swaths, like ROSE-L with up to 260 km swath width [19], bringing the total raw data well over 1 Gbit/s.

Given the high resolution of modern SAR sensors, the raw data volumes are extremely large, and increasing for every new generation of missions. Fig. 2 illustrates some examples of the evolution of SAR missions, highlighting the significant data volumes produced. Sentinel-1 stands out, generating approximately 90 GB per orbit, downlinked using an X-Band polar station and an optical geostationary relay satellite. This data is transferred to ESRIN, ESA center in Rome, where it is processed into Level 0 products within three hours post-acquisition, and Level 1 products within a day [20]. Earlier missions like ERS-1 and ERS-2, despite their high data acquisition rate, lacked onboard storage, necessitating direct data capture within the ground station range [21]. The successor of the ERS-1 and ERS-2, the Envisat satellite, launched by ESA in 2002, was equipped with an Advanced SAR (ASAR), and its communication system allowed the recording and transmission of high-rate data, including the Low Bit Rate (LBR) global data and the Medium Resolution Imaging Spectrometer (MERIS) Full Resolution (FR), further detailed in the Appendix. Envisat's on-board recording system included two solid-state recorders (SSRs) and a tape recorder of 30 GB for low-rate data. These recorders facilitated the handling of the satellite's high data rates and complex mission operations, ensuring efficient data recovery and transmission for EO purposes [22].

Fig. 1: TanDEM-X and TerraSAR-X in formation flight [25].

TerraSAR-X and TanDEM-X, twin satellites launched by the German Aerospace Center (DLR) in 2007 and 2010 respectively, exemplify the advancements in SAR technology and data handling capabilities. Flying in close formation, these satellites are dedicated to generating highly precise digital elevation models of the Earth's surface, surpassing previous SAR missions in terms of resolution and data accuracy. TerraSAR-X is capable of producing imagery with resolutions down to 1 meter, generating significant data volumes [23]. The TanDEM-X ad-on mission, performs innovative interferometric techniques, allowing for the collection of data with unprecedented accuracy in three-dimensional models of the Earth's terrain [24]. The formation flying aspect, illustrated in Fig. 1, enables data acquisition from slightly different angles, providing interferometric SAR measurements. The synergy between TerraSAR-X and TanDEM-X highlights the increasing complexity and volume of data being managed, with applications such as topography, geology, hydrology, and vegetation monitoring.

Umbra is set to release imagery from its tandem pair of SAR satellites, introducing bistatic SAR data to its offerings in 2024. The company successfully launched its first tandem pair of satellites, Umbra-07 and Umbra-08, on the SpaceX Transporter-9 mission in November 2023. With eight satel-

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lites already in orbit, Umbra aims to complete its licensed 32-satellite constellation by deploying satellites in pairs to enhance multistatic collection and integrated operations. This strategy is expected to enhance Intelligence Surveillance Reconnaissance (ISR) capabilities, elevation modeling, imaging resilience, and the implementation of moving target indication techniques [26].

Umbra's progress in technology for automated formation flying and multistatic data processing has been accelerated by its partnership with the Defense Advanced Research Projects Agency (DARPA) as part of the Distributed Radar Image Formation Technology program. This advancement allows for the potential proliferation of resilient systems offering both traditional and full spectrum capabilities. Umbra's SAR satellites provide high-quality SAR data at unprecedented volumes, supporting the needs of the U.S. Government, its allies, and commercial partners with actionable insights [26].

COSMO-SkyMed and RADARSAT are smallsat constellations formed by 4 and 3 satellites respectively. COSMO-SkyMed is an Italian constellation owned by Agenzia Spaziale Italiana (ASI) and collects SAR data in X-band, offering high-resolution imagery for applications such as environmental monitoring, disaster relief, and defense [27]. RADARSAT Constellation Mission (RCM) is formed by 3 identical owned and operated by the Canadian Space Agency (CSA), designed to provide continuous monitoring of Canada's land and oceans, as well as daily access to 95% of the world to support a wider range of applications [28].

Future missions like ROSE-L will generate an order of magnitude more data daily compared to Sentinel-1 and therefore target onboard mass memories in the order of tens of Terabits to ensure an operational duty cycle [16]. These sizes and densities have been made possible thanks to the use of commercial FLASH memories as base technology, replacing DRAMS (in Sentinel-1), or old tape recorders (Envisat).

As new missions are launched, their downlink capacities keep improving, even for small satellites. For example, NovaSAR-1, launched in 2018, reaches a downlink rate of 400Mbps through an X-band frequency band [29]. The operational strategies for these missions reflect adaptations to technological capabilities and mission objectives.

A. Storage efficiency

Compression plays a crucial role in addressing the challenges associated with large data volumes. Efficient compression algorithms are needed to store data on-board and to ensure operational flexibility, the handling of communication interruptions due to diverse atmospheric and technical reasons, and the optimization of the power use, effectively extending the satellite's operational window. Vast amounts of raw data, due to the high spatial resolution that SAR systems offer, need to be stored before transmitting or processing. Efficient on-board data storage is crucial due to bandwidth and downlink constraints, and it allows for the data to be saved and transmitted in batches or during an optimal communication window [30]. Moreover, it provides flexibility in data handling: while some processing can be done on-board for immediate applications, data needs to be stored for more detailed post-processing on the ground station. By efficiently storing data on-board, resource allocations can be optimized and managed, thereby enhancing operational efficiency. Adaptive sampling in on-board SAR processing tailors data collection and retention based on the characteristics of the area being imaged. The concept leverages the ability of SAR systems to dynamically adjust their data acquisition strategies in response to the observed environment, based on the following principles:

1) Selective data retention: efficient algorithms like Block Adaptive Quantization (BAQ), which adjust the quantization levels based on the information content of different areas, are used. The goal is to ensure that critical data is retained with higher fidelity, while less important data is compressed more aggressively. For instance, open ocean and big cities have different needs for compression, with big cities needing the retention of more details than the sea [31].
2) Area of interest identification: adaptive compression in SAR systems can be based on real-time identification of important areas, through mission-specific criteria or instant data analysis. A SAR system may focus on collecting detailed data over busy maritime areas and employ simpler methods for less active open ocean regions [32].
3) Algorithmic implementation:adaptive sampling implementation in SAR processing often involves algorithms capable of real-time decision-making. These assess the current data, compare it against the mission criteria, and adjust the sampling strategy as needed. ML techniques, particularly those capable of on-the-fly learning and adaptation, are increasingly being used for this purpose [32].

While adaptive sampling presents significant advantages in data management and resource optimization, it also introduces challenges. These include the need for robust algorithms capable of operating in diverse and changing environments, the risk of overlooking important data due to pre-set criteria, and the computational demands of real-time data processing.

B. Transmission efficiency

Compressed data requires less bandwidth, ensuring quicker data downlink and reduced transmission costs. For applications such as disaster response, real-time or near-real-time access to SAR data is crucial. Efficient transmission allows for quicker access to the data on the ground [33]. In 1999, ESA and France's CNES space agency started a service called International Charter Space and Mayor Disasters, joined by the CSA in 2000. When a catastrophe happens, a petition can be submitted by pre-defined disaster risk management authorities from all over the world to redirect a satellite to map the area where the disaster has happened. Once activated, the charter members coordinate their efforts to task their satellites to acquire relevant data over the affected area [34]. While the charter ensures that satellite assets are mobilized in the wake of disasters, the efficiency of SAR data transmission ensures

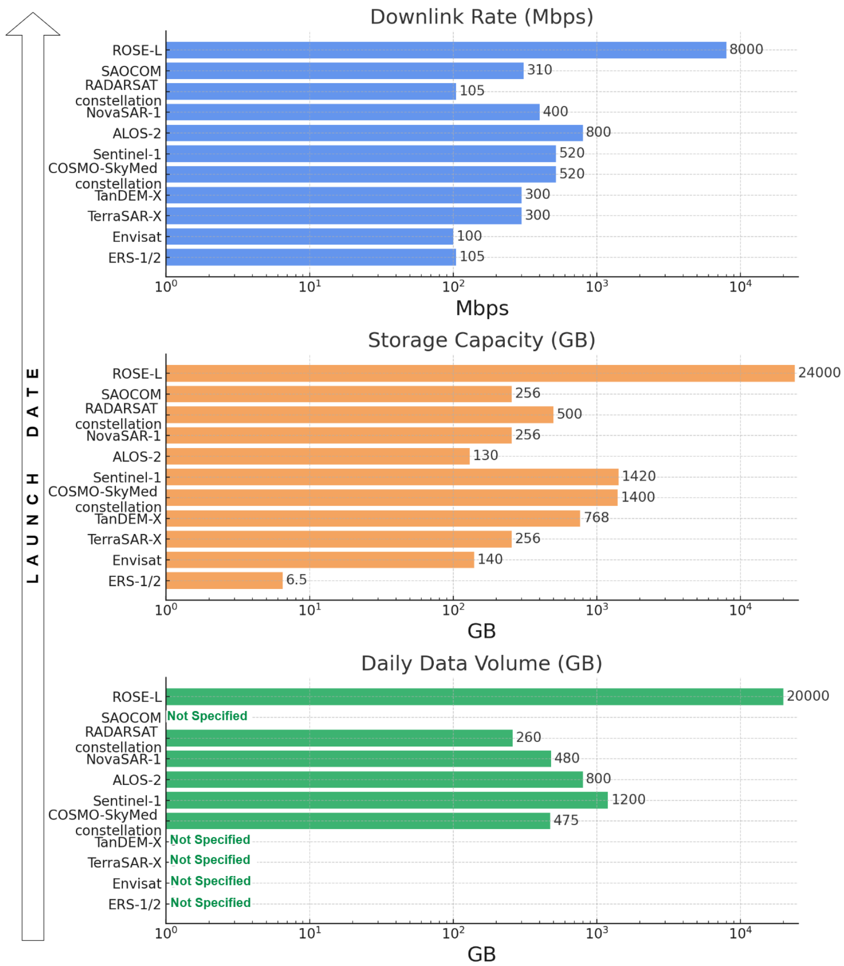

Fig. 2: Comparative analysis of downlink rates, storage capacities, and daily data volumes across SAR satellite missions.

that the data captured is swiftly and reliably delivered where it is needed.

The SAOCOM mission, a major initiative by the Argentine National Commission for Space Activities (CONAE), involves deploying two satellite constellations, SAOCOM 1 and 2, with each comprising two satellites (A and B). These constellations, along with the Italian COSMO-SkyMed satellites, form the Italian-Argentine Satellite System for Emergency Management (SIASGE). The system represents a significant advancement in managing environmental emergencies and providing crucial satellite information beneficial for various applications, including disaster response [35]. Developed within the framework of Argentina's National Space Plan, SAOCOM 1A exemplifies a significant technological achievement, representing collective efforts involving more than 100 technology-based companies and numerous institutions. The satellite carries a high-performance L-band SAR, making it one of the most advanced SAR satellites at the time of its launch. The revisiting period is 16 days for one satellite and 8 days for the entire constellation. Its capabilities are particularly noteworthy in the context of vegetation index and pest control in agriculture, hydrological and oceanic studies, and monitoring snow, ice, and glaciers. It also has significant applications in urban planning, security, defense, and other productive industries such as mining and energy [14].

As on-board data processing evolves, the volume of data that needs to be transmitted is reduced and techniques like filtering, feature extraction, and preliminary analysis play a key role in transmission efficiency. Feature extraction involves identifying and isolating significant features within the SAR data, such as edges, textures, or specific patterns. This process is crucial for target recognition, land cover classification, and change detection. Preliminary analysis refer to the initial interpretation and processing of SAR data on-board the satellite. This step can include basic image formation [36], geolocation tagging, and the identification of areas of interest.

C. Processing techniques

Modern SAR systems face challenges regarding the limitations in size, weight, power, and cost (SWaP-C). As they become more complex and produce larger volumes of data, the need to transfer the data to the ground stations for processing requires effective compression algorithms. However, these algorithms can cause degradation and losses, potentially reducing the effectiveness of the missions [37]. To evaluate the performance and trade-offs of different compression techniques, two key domains can be analyzed: the data domain and the image domain. In the data domain, the metrics used for the analysis are compression ratio, dynamic range, signal-to-quantization-noise ratio, and statistical parameters. Through these metrics, the compression algorithm's impact on the raw data quality and fidelity can be studied. In the image domain, the focus shifts to evaluating the quality of SAR outputs post-processing. Higher-order statistical parameters and image quality measures need to be These parameters are listed in Table I.

Suitable compression algorithms must be selected during the design phase of SAR systems based on the specific SAR technology and applications, and the inherent characteristics of SAR data, especially in light of SWaP-C limitations. Furthermore, the computational complexity of compression algorithms is a vital consideration for practical implementation in constrained SAR system environments [37].

Regarding the information loss caused by processing steps such as compression, Shannon's theory, particularly his concept of entropy in information theory, is highly relevant. Shannon's entropy H is a fundamental measure in information theory that quantifies the expected value of the information contained in a message, in units such as bits. It is given by the formula:

$$H(X) = -\sum_{i=1}^{n} P(x_i) \log_b P(x_i) \tag{1}$$

where X is a discrete random variable with possible outcomes $x_1, x_2, ..., x_n$, $P(x_i)$ is the probability of outcome x_i, and b is the base of the logarithm used. Commonly, the base 2 logarithm is used, which results in an entropy value measured in bits.

In SAR data processing, each pixel's value can be considered a message, and the set of possible pixel values across an image—or a set of images—forms the probability distribution needed to calculate entropy. Higher entropy in a SAR image means more randomness and less predictability in pixel values, reflecting more complex surface features or textures. Low-entropy images may contain a lot of redundant information or fewer features, which makes them more compressible without significant loss of information. However, the entropy of a SAR image is not just a measure of randomness; it is also a measure of information content. High-entropy images are information-rich, full of details significant for interpretation and analysis. When compressing such data, especially with lossy compression techniques, it needs to be done with care to preserve the significant features.

The relationship between entropy and compression is also governed by the source coding theorem, part of Shannon's information theory. It states that, for a given source (in this case, a SAR image), there exists an encoding scheme that can compress the data to $H(X)$ bits per symbol on average, where $H(X)$ is the entropy of the source. Therefore, an optimal compression algorithm would achieve compression rates approaching the image's entropy without losing significant information [38]. This is where the challenge lies in SAR data processing, designing compression algorithms that are as close to this theoretical limit as possible, without compromising the integrity of the data.

Algorithmic information theory (AIT) or *Kolmogorov complexity* gives a quantitative, non-probabilistic approach to the definition of information and can be applied to the SAR domain. AIT derives its name from the concept of information, as first introduced by Shannon's information theory, and the use of algorithms or programs to measure the content of information [39]. When dealing with the diverse and complex SAR data, AIT can enhance the analysis and understanding of EO images, addressing the challenges posed by traditional image analysis methods that rely on predefined data models, parameters, and probability density functions. AIT offers a parameter-free, data-driven approach that leverages the computational complexity of image data for analysis. By approximating Kolmogorov complexity through data compression algorithms, AIT-based methods can effectively reduce the size of SAR datasets while preserving the informational content. This facilitates more efficient storage and transmission of SAR data [40].

SAR systems capture raw IQ data that contains information about the reflected radar signals from the Earth's surface. To get the final product, the data undergoes a series of processing steps. In the case that the final product requires the formation of a full image, among these processing steps, range and azimuth compression, range-Doppler terrain correction, and speckle reduction can be highlighted. While range and azimuth compression retain the essential information, the geometry terrain correction alters some information about the original geometry, which affects the entropy in the data, as it changes the degree of uncertainty within it. Moreover, speckle reduction, although it improves image clarity, can potentially remove some fine details, leading to loss of information [41]. In some scenarios, particularly in interferometric applications, where maintaining the accuracy of phase information in complex image data is crucial, it is necessary to minimize data compression, which needs to be lossless or near-lossless. This approach ensures that the integrity of the phase details is preserved. Shannon's theory highlights the importance of retaining high entropy in the data to maintain all the original information in these scenarios.

Conversely, for tasks like global monitoring or identifying human-made structures, it can be feasible to employ more aggressive data compression techniques. These applications can tolerate a significant reduction in data entropy [42]. There needs to be a balance between the level of entropy reduction and the application's tolerance for information loss. Depending on the domain that the compression is performed in, algorithms for SAR raw data compression can be divided into two categories: spatial domain compression techniques, like BAQ [31] or variations like the Flexible Dynamic BAQ (FDBAQ) [43] and transform domain, which include transforming the data before applying BAQ compression, like the Fast Fourier Transform BAQ (FFT-BAQ) [44] or the discrete cosine transform BAQ (DCT-BAQ) [45].

Balancing data integrity and data volume reduction is a critical aspect of SAR data processing. It's uncommon for end-users to have significant input into mission design, which often hinders accurately defining the acceptable level of information loss based on their specific application requirements. Ultimately, the data undergoes varying processing and compression steps depending on its intended use. For scenarios where actionable data, such as event location coordinates or displacement-triggered change flags, requires near-real-time downlinking to end-users, compression may not be necessary. Since the data size is often quite small, compression would risk information loss. Additionally, bypassing compression expedites data processing, enabling faster delivery.

TABLE I: Evaluation metrics of the quality of SAR data compression in the image and the data domains.

Visual Fidelity	• **Subjective Evaluation:** Involves human observers rating the image quality based on clarity, sharpness, and presence of artifacts. Subjective and varies between observers. • **Reference-Based Metrics:** Comparison between the compressed the compressed and the original images.
Quantitative Metrics in Image Domain	• **Impulse Response Function (IRF):** The less distortion in the IRF, the better fidelity in the SAR image [37]. • **Peak Signal-to-Noise Ratio (PSNR):** Measures the peak error between the compressed and original images [46]. • **Structural Similarity Index Measure (SSIM):** Evaluates changes in structural information, luminance, and contrast. It can be combined with texture information (TSSIM) [47]. • **Contrast metrics:** Image Contrast (IC), and Global Contrast Factor (GCF) [37]. • **Statistical parameters:** Entropy, mean, standard deviation, skewness, and kurtosis [37]. • **Compression Ratio vs. Quality Loss:** Analyzes the trade-off between compression degree and image quality loss [48].
Quantitative Metrics in Data Domain	• **Statistical parameters:** Entropy, dynamic range, mean, standard deviation, skewness, and kurtosis [37]. • **Compression Ratio**. • **Data histograms:** Comparison of the distributions of the phase, quadrature, magnitude, and phase components before and after compression [37]. • **Error measures:** Mean Square Error (MSE), Mean Phase Error (MPE), and Signal-to-Quantisation-Noise Ration (SQNR) [37].
Impact on Analysis Tasks	• **Target Detection Performance:** Assesses how compression affects the ability to detect and classify objects. • **Classification Accuracy:** Evaluates the impact of compression on classification accuracy. • **Feature Extraction:** Investigates the effects of compression on the extraction of features critical for analysis.

D. Compression and pattern recognition

Pattern recognition based on data compression explores how patterns within data can be identified and understood through compression. This approach advantages the principle that data exhibiting regular patterns can be compressed more efficiently, suggesting that highly compressible data indicates a greater degree of pattern or regularity.

1) Pattern representation: In [49], Normalized Compression Distance (NCD) is introduced to clarify the application of compression-based algorithms for remote sensing. The NCD algorithm helps identify similarities between objects by evaluating how well they compress together, indicating shared information. This principle can be applied across various data types, including spectral signatures from hyperspectral sensors and SAR images. The Pattern Recognition based on Data Compression (PRDC) methodology is also introduced, highlighting its relevance to EO data analysis while distinguishing it from the NCD. PRDC focuses on dictionary extraction and the use of these dictionaries for compressing other data, facilitating the identification of similarities. PRDC has been employed to automatically cluster airborne images and segmentation of satellite images. Despite their differences, both PRDC and NCD are instrumental in remote sensing, with the choice between them depending on the specific application's demands for speed and accuracy [50].

2) Conditional compression: The concept of conditional compression, $C(x|y)$, is crucial for understanding how to efficiently process and store large volumes of EO data, especially given the rapid increase in data acquisition in recent years. This compression metric represents the size of the compressed version of a dataset x when another dataset y is available as an auxiliary input, effectively measuring how to encode x with knowledge of y. Delta encoding is particularly relevant for handling satellite or aerial imagery data. This method compresses data x by only storing the differences with dataset y, taking advantage of the fact that subsequent acquisitions often cover the same geographical areas. By finding common strings or sequences between x and y, using techniques like the Longest Common Subsequence (LCS) method or edit-distance methods, delta encoding efficiently captures only the changes or differences, allowing for the full recovery of x with access to y. The application of delta encoding in the context of EO data is significant due to the growing volume of data and the frequency of repeated area coverage. By storing only the compressed differences between two datasets acquired at different times, delta encoding facilitates efficient storage and direct comparison. This approach not only saves storage space but also reduces computational overhead, since the computation of $C(x|y)$ is implicit and readily available for future analyses, enhancing the capability to monitor, analyze, and interpret changes in the Earth's surface over time [49].

3) AI-based processing: Recent advancements in Deep Neural Networks (DNN) have opened new avenues for SAR data compression. Using DNN-based methods and complex patterns, correlations can be learned in the data, enabling highly efficient compression schemes. Furthermore, the incorporation of side information, such as auxiliary data from other sensors or previous SAR missions, can improve the compression algorithm's performance. Aiming to reduce the data volume while maintaining the quality of the reconstructed image, a novel compression scheme that pre-processed the raw data before applying NN-based compression is proposed in [51]. The approach is called Back Propagation Neural Network (BPNN) and applies an adaptive learning rate to minimize the MSE, showing promising results, with SNR improvements of various bits per sample rates, demonstrating that BPNN can effectively compress SAR raw data beyond the capabilities of conventional methods, like BAQ. The NN-based compression algorithm outperforms traditional techniques and offers a feasible solution for on-board SAR data compression, potentially alleviating storage and transmission challenges for future high-resolution SAR satellites.

In [52], the development and implementation of an AI-based method for optimizing the quantization of SAR raw data in next-generation systems is presented. The proposed method, Performance-Optimization BAQ (PO-BAQ), extends the basic concept of BAQ by incorporating an ML-based architecture to dynamically generate bit rate maps for data compression, depending on the performance requirements of the products. A U-Net architecture is used for bit rate maps generation, demonstrating feasibility with preliminary results, tested using TanDEM-X bistatic land data.

In the field of maritime surveillance, the main limitations are satellite-ground communication and the sheer quantity of data. In [53], an on-board processing scheme is proposed combining the traditional Constant False Alarm Rate (CFAR) method with lightweight deep learning, specifically, the You Only Look Once version 4 (YOLOv4), to enable near real-time on-board image processing and data transmission. This approach applies CFAR for initial ship detection, followed by YOLOv4 for refined results, achieving significant improvements in processing time and accuracy (85.9% precision on experimental data) compared to traditional methods. The scheme is validated through a ground verification system and makes use of embedded GPUs for high efficiency. This method represents a significant step forward in advanced computing and AI techniques for on-board satellite image processing, offering a faster and more accurate solution for maritime surveillance applications.

The push for miniaturized and efficient computing platforms, like the Myriad 2 vision processing unit (VPU) developed by Intel, offers a potent solution for real-time data processing in EO missions. the reconfigurability of COTS AI platforms and the development of compact deep learning models offer a pathway to overcome the obstacles that on-board AI-based processing faces, allowing for greater autonomy, enhancing their operational capabilities, and opening new possibilities for space-based observations and data analysis [54].

E. Space-ground edge computing

Edge computing is developed to enhance cloud computing, incorporating cloud features at the network edge. This approach moves computing and storage closer to mobile users, enabling more efficient processing of mobile tasks with reduced transmission latency and easing the load on the central network's data transmission [55]. The integration of satellite-based and ground-based edge processing, alongside AI/ML capabilities, represents a significant advancement in data management and analysis within Space-Air-Ground Integrated Networks (SAGIN). This innovative approach uses on-board processing units on satellites to perform immediate data

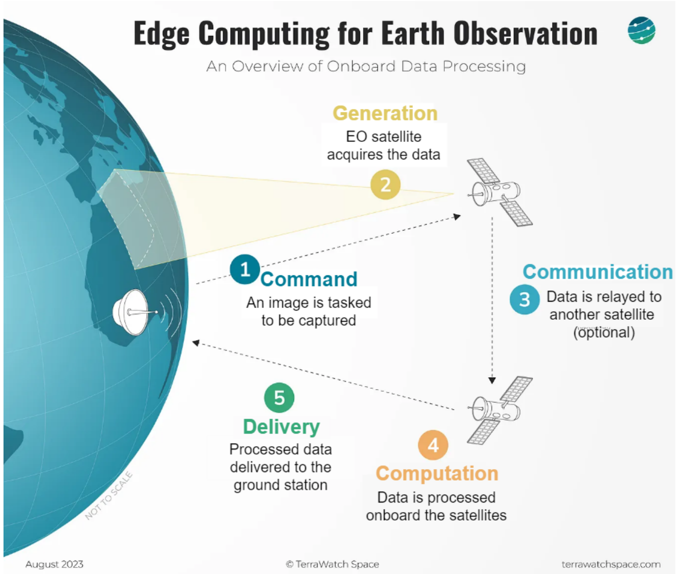

Fig. 3: Overview of edge computing for EO [57].

filtering and compression, substantially reducing the volume of data that needs to be transmitted back to Earth. Doing so conserves valuable bandwidth for additional transmissions and minimizes the costs associated with data downlink. In Fig. 3, a simple representation of the process of edge computing in EO is displayed, detailing the sequence from satellite tasking through onboard data processing to the eventual transmission of the requested data to the ground station.

On the ground, the deployment of edge servers near receiving stations enhances this process by further refining the data before its transmission to the cloud. This strategic placement markedly decreases latency, thereby facilitating quicker data analysis and decision-making.

The incorporation of AI/ML algorithms into both space and ground edge nodes transforms these systems into intelligent platforms capable of conducting real-time analysis of SAR data. This capability enables automated identification and classification of targets, the detection of anomalies signaling potential threats or events, and significantly faster response times.

SAGIN's architecture harmonizes satellite constellations, aerial networks, and ground communication to enhance data collection and processing across various domains. This cohesive framework bridges the gaps inherent to individual layers and takes advantage of their unique strengths. Effective communication within and between these layers, facilitated by the integration of AI/ML, is crucial for ensuring seamless integration and collaborative operation, underpinning the development of a wide range of services and applications [56].

F. Challenges and limitations

With the increasing demand for real-time or near-real-time data processing, on-board SAR data processing has emerged as a vital research area. While promising, this approach is fraught with challenges and limitations. SAR data processing, for

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example in the case of high-resolution imaging, involves computationally intense operations. When performed on-board, there are constraints due to limited processing power, particularly when compared to ground-based infrastructures [58]. Two critical parameters that significantly influence on-board processing are latency and revisit time.

The evolution of SAR satellite system architectures is shifting from using single or pairs of satellites to deploying extensive constellations. This transition enhances the robustness, reliability, and resilience of the systems, while also boosting performance. Improvements include increased tasking capabilities and a reduction in the data delivery time [32]. The shift in SAR satellite system architectures towards large constellations is closely linked to the rise of smallsats (small satellites). These smaller, more cost-effective satellites are integral to forming large constellations, offering numerous advantages:

- Latency in on-board processing: low latency is crucial for timely data delivery, essential for applications like disaster response, ocean surveillance, and agricultural monitoring [59]. Smallsats often have limited processing capabilities and downlink bandwidth. To manage latency, advanced on-board processing algorithms are implemented that balance the trade-off between data compression (to reduce downlink volume) and data integrity. Edge computing and AI-driven approaches are being explored to enhance on-board processing efficiency. Low-latency systems enable rapid decision-making and timely interventions [60].
- Revisit Time: this is a vital parameter for smallsat constellations, as it determines the temporal resolution of the SAR system. Shorter revisit times allow for more frequent monitoring, essential for dynamic EO tasks. Smallsat constellations have revolutionized revisit capabilities [61]. Deploying a range of small satellites into various orbits, as illustrated in Figure 4, enables revisit times of a few hours or less. This marks a considerable enhancement compared to the longer intervals typical of conventional, SAR satellites [62]. Frequent revisit capabilities are crucial in areas that need to be constantly monitored, for example, areas suffering deforestation, ice movements, landslides, or to monitor crop health.

The combination of low-latency data processing and frequent revisits enables comprehensive, near-real-time analysis of large geographical areas. This integration is key for predictive analytics and long-term environmental monitoring [63]. Continued advancements in SAR sensor technology, data compression methods, and on-board computing power are essential to enhance the capabilities of SAR EO and smallsat SAR systems. Developments in ML and AI will play a significant role in automated data processing and anomaly detection [64].
Smallsat constellations offer numerous advantages, but they also pose challenges in terms of orbital and data management as well as signal interference. In Table II, a comparison between smallsats and large flagship satellites is shown, highlighting the advantages, applications, and on-board processing capabilities among other features. Addressing these challenges requires coordinated efforts in space traffic management and ground segment infrastructure [65]. Smallsat SAR constellations open up new avenues for collaboration between governments, private entities, and research institutions, and present commercial opportunities [66]. The use of advanced processing techniques "on the edge" for EO has been in discussion for quite a while (see [67] for the first in this field), and in this domain, the EO-ALERT project aims to revolutionize EO by shifting key data processing elements from ground to on-board satellites. This architecture significantly reduces data delivery latency, aiming for a latency of less than 1 minute with a maximum below 5 minutes for SAR and optical image products.
The innovation encompasses on-board reconfigurable data handling, image processing using AI, and high-speed data transmission, including separate channels for urgent alerts. The project also explores ship detection and extreme weather now casting scenarios, demonstrating the potential of this architecture to deliver rapid civil alerts. The technological advancements include high-speed avionics, AI-based data compression, and advanced communication links, proving the feasibility of the EO-ALERT concept for timely EO product delivery [68].

In the context of high-speed communications advances, The Space Data Highway was developed as a pioneering optical communication system based on advanced laser technology as a collaborative effort between ESA and Airbus. The system incorporates laser communication terminals developed by Tesat-Spacecom and the DLR German Space Administration. It enables high-speed data transfer, including images, voice, and video, from LEO satellites and airborne platforms to ground stations across Europe via geostationary satellites EDRS-A and EDRS-C. Revolutionizing space communications, the Space Data Highway can transfer data at speeds up to 1.8 Gbit/s in near-real time. It receives data from LEO EO satellites traveling at 26,000 km/h at 700 km altitude and relays it via its two geostationary satellites at 36,000 km to Earth. The system can download 230GB of data in an average session of 18 minutes and relay up to 40 terabytes daily [69].

G. Hardware improvements and accelerators for on-board processing

The advancements in hardware for on-board processing in SAR systems are crucial for enhancing the efficiency and speed of data processing in space. However, the harsh environment of space, with its extremes of temperature, radiation, and vibration, can put significant stress on electronic components, increasing the risk of failure. As a result, space agencies and satellite manufacturers are very cautious about adopting new technologies that have not been thoroughly tested and proven reliable. Some key developments in this field are:

- FPGAs: FPGAs have become a significant focus in on-board satellite processing due to their flexibility and efficiency, and the fact that new FPGAs integrate high speed serial links and a good deal of embedded memory (like Xilinx VERSAL ACAP) makes them an ideal solution [72]. In [73], a novel methodology for integrating FPGA accelerators into on-board SAR processing systems. The

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Fig. 4: SmallSat constellation representation.
Note: this image was created with the assistance of DALL·E 2, OpenAI

TABLE II: Comparison Between Large Satellites and Smallsats for EO [70], [71]

Feature	Large Satellites	Smallsats
Mass	Usually over 1,000 kg	500 kg to 1,000 kg
Design Complexity	High, with more functionalities	Simplified, focusing on specific missions
Cost	Very high, including development, launch, and operation	Significantly lower, enabling more frequent updates and larger constellations
Launch Flexibility	Limited, often requiring dedicated launches	Higher, can piggyback on other launches
Development Time	Long, often several years	Shorter, benefiting from COTS components
Orbit	Predominantly Geostationary Earth Orbit (GEO) or High Earth Orbit (HEO) for comprehensive coverage	Mainly LEO for reduced latency and cost
On-board Processing Capabilities	Advanced, with higher power and computing resources to support complex missions	Limited by size and power constraints, though advancing rapidly with technology
Constellation Capability	Typically operates as standalone or in small constellations due to cost	Enables large constellations for frequent revisits and real-time coverage
Application Scope	Broad, covering a wide range of EO applications	Focused, with specific applications such as biospheric monitoring, disaster management, and maritime tracking

approach involves using High-Level Synthesis (HLS) for creating Intellectual Property (IP) blocks and the Reusable Integration Framework for FPGA Accelerators (RIFFA) for developing a high-speed Peripheral Component Interconnect Express (PCIe) interface. HSL transforms high-level programming languages into Hardware Description Language (HDL), reducing development time and allowing optimizations [74]. The proposed interface allows transfer rates up to 15.7 GB/s between the Central Processing Unit (CPU) and the FPGA. HLS and RIFFA reduce development time significantly by using high-level programming languages and providing optimizations, like pipeline, cyclic partition, and unroll. This methodology is flexible and scalable, enabling the exchange of IPs for different processing routines and using up to five FPGAs with multiple IPs in each. To highlight the complexity of SAR image synthesis algorithms and the advantages of FPGA technology for real-time applications in SAR imaging, a real-time SAR image processor using FPGAs is developed in [75]. The approach is based on leveraging the improved speed and density of FPGA devices, using Commercial Off-the-shelf (COTS) hardware for processing the SAR signals. Tests demonstrate the processor's capability to generate SAR images in real-time with satisfactory quality, despite the complexity of the task, using a relatively low degree of FPGA logical resources (about 30%), with higher usable block memory (RAMB) [75].

- Multi-Processor System-on-Chip (MPSoC) Technologies: The integration of multi-core processing systems and programmable logic units in MPSoC devices is a significant step forward. This integration allows for the effective handling of SAR processing algorithms directly on the satellite, making real-time data processing and rapid generation of SAR imagery more feasible [76]. MPSoC devices facilitate easy implementation and enable the execution of less urgent computations on a CPU. Meanwhile, intensive signal processing tasks are efficiently handled by designing them as pipelined streaming circuits within FPGA hardware [77]. Such systems can handle various data types from multiple sensors over a wide range of dataset sizes, proving beneficial in scenarios like ship detection and extreme weather monitoring [78].
- Reconfigurable Accelerators: Reconfigurable accelerators are designed to enhance the processing capabilities of SAR systems, thereby enabling more complex and efficient data processing tasks. They are an innovative approach that combines the flexibility and programmability of hardware like FPGAs and MPSoC devices. Their accelerators are designed to adapt to different SAR processing needs while maintaining low latency and efficient power consumption [78]. The concept of reconfigurable accelerators is particularly advantageous in SAR processing due to the varying nature of SAR data and the need for rapid processing in different scenarios [79]. They can be dynamically reconfigured to adapt to different processing requirements, such as varying PRF, pulse lengths, bandwidths, and elevation beams [80].

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- Use of COTS Components: The incorporation of COTS components, in conjunction with space-qualified parts, optimizes the balance between performance, cost, and reliability. This allows for the utilization of state-of-the-art technology and processing power while maintaining the robustness required for space applications. This strategy is crucial for keeping the weight, volume, and cost of Payload Data Processing Units (PDPUs) low compared to an all-space-grade design. A growing number of initiatives and projects are promoting the extensive adoption of COTS EEE components to fulfill demanding requirements related to SWaP, always understanding the risks and extensively testing these parts [81].
  Historically, NASA has used specific classes of military specification (MIL-SPEC) parts as "standard" for their projects, typically employing these parts directly without additional testing. In contrast, nonstandard parts, including COTS components, underwent initial screening and lot acceptance testing based on MIL-SPEC or similar criteria. Over the years, top commercial part manufacturers have made significant advancement in manufacturing quality, statistical control, and technology. This evolution has led to COTS parts sometimes being as reliable, or even more so, than MIL-SPEC parts, especially when used within their specified limits. This shift is driven by the space science and exploration community's need for technological advancements not available with MIL-SPEC parts [82].

These advancements are integral to overcome the challenges associated with SAR on-board processing, such as handling the high data rates and complex algorithms required for SAR data processing. The developments in FPGA utilization, MPSoC technologies, reconfigurable accelerators, and the strategic use of COTS components, collectively contribute to the significant improvement in SAR systems' efficiency, speed, and overall performance in space-based EO missions.

III. Real-time Capabilities

Despite its advantages, real-time processing of spaceborne SAR data poses significant challenges. These include the handling of large volumes of data, the computational complexity of SAR processing algorithms, and the limitations in on-board computing power and data transmission capabilities. Overcoming these challenges often involves the integration of advanced data compression techniques, efficient algorithms, and high-performance computing resources.

A. Strategies for real-time SAR processing

Strategies for real-time SAR processing are crucial for efficient and effective handling of the large volumes of data that SAR systems generate. These strategies involve specialized hardware and software approaches to meet the demand for real-time processing. Designing a specific heterogenous array processor is an effective approach for real-time SAR imaging, particularly when dealing with large input images. This method helps in meeting the power consumption constraints and real-time processing requirements of SAR systems [83]. In the context of SAR image formation, a novel approach in real-time SAR processing involves the adoption of a time-domain subaperture method. This technique is uniquely suited for real-time processing and capable of generating high-quality, full-resolution images, which is especially beneficial in scenarios where the immediate production of images is of great importance [84]. Fast processing enables timely decision-making based on the most current information available.

Exploiting the computing resources of CPUs and GPUs in a parallel strategy to realize real-time algorithms, can significantly enhance the speed and efficiency of SAR data processing [85].

B. Parallel processing and efficiency enhancement

With the use of FPGAs, the algorithms are more easily parallelizable and they are significantly more powerful than GPUs and Cell processors, very important in airborne applications and real-time data processing. Recent advancements in hardware and software have significantly impacted real-time signal processing, particularly with the introduction of specialized processing architectures and devices. FPGAs stand out due to their programmability, parallel processing capabilities, and energy efficiency. Enhancements in high-level language synthesis for FPGAs have further streamlined programming algorithms. For SAR imaging, the Back-Propagation (BP) algorithm, known for its intensive computational demands, benefits from the FPGA's programmable, parallel multi-pipeline architecture, allowing for more efficient implementation. Recent research has focused on optimizing the BP algorithm using FPGAs, including methods to simplify interpolation and integrate fixed-point data processing via the OpenCL framework for improved performance. However, these developments still face challenges in enhancing processing time efficiency [86].

C. Calibration

Calibration of on-board SAR systems and the detection of malfunctions before data downlink are critical aspects of ensuring data quality and operational reliability. The integration of AI techniques can significantly enhance these capabilities. Calibration involves adjusting system parameters to compensate for hardware imperfections and environmental factors. On-board calibration methods include the use of internal calibration devices within the radar system to track performance changes over time, compared to pre-launch calibrations. Externally, monitoring ground targets with known characteristics offers a comprehensive system check [20]. AI can enhance calibration by continuously analyzing data quality and system performance, and automatically adjusting calibration parameters in real-time. Detecting malfunctions in SAR systems before data transmission is crucial to prevent the loss of valuable data and time. ML algorithms can be used to monitor system health, identify anomalies, and predict potential failures. This predictive maintenance ensures that issues are addressed proactively, reducing downtime and improving system reliability. AI can implement adaptive algorithms that dynamically adjust their complexity based on available computational resources and data characteristics, optimizing processing efficiency.

A summary of SAR missions, data handling, and advancements is presented in Table III, in the Appendix, to encapsulate the concepts and the key information discussed throughout the section.

IV. Artificial intelligence and SAR data

The use of AI is becoming increasingly crucial in managing the vast volumes of data generated by SAR systems, especially with the advent of low-cost micro-satellites that are enhancing EO capabilities. Companies like ICEYE are at the forefront of building these micro-satellites equipped with SAR and focusing on the application of AI techniques to enhance data quality, collaboration, and various applications in line with ESA guidelines [87].

One of the primary benefits of incorporating AI in SAR technology is its potential in on-board processing. AI can significantly reduce the volume of data that needs to be downlinked by processing it on-board. This enables the implementation of dedicated detection algorithms directly on the satellite, leading to more efficient data handling and reduced processing time. Such advancements are crucial for handling the large amounts of data generated by the ICEYE X-band EO data and other similar technologies [88]. The calibration and validation processes, which are essential for ensuring the quality and accuracy of SAR data, are also being enhanced through AI integration.

Moreover, the implementation of AI-driven processing techniques on-board SAR-equipped satellites helps in the rapid processing of large data volumes. This not only reduces the unnecessary transmission of data to ground stations but also ensures that the quality of the data is maintained. After the calibration and validation phases, EO data providers need to characterize the quality of the data provided. Companies like ICEYE are conducting quality assessments on X-band SAR data and developing both on-board and on-ground processing techniques based on AI, thereby setting a new standard in SAR data processing and analysis [88].

A. Data availability and accessibility

The global SAR market has grown substantially, reaching a size of US$ 3.8 Billion in 2022, and is expected to reach US$ 7.0 Billion by 2028. This growth is driven by escalating demand for EO and remote sensing capabilities, widespread adoption of SAR systems in commercial sectors like agriculture and mining, and rising geopolitical concerns [89]. In recent years, the availability and accessibility of SAR data to the public, including companies and individual users, have improved significantly due to various initiatives and platforms that facilitate easier access to the data.

NASA has been actively working to make SAR data more accessible and user-friendly. The Jet Propulsion Laboratory (JPL) and the Alaska Satellite Facility (ASF) have collaborated on projects like the Advanced Rapid Imaging and Analysis (ARIA) Project and the NASA-funded Enabling Cloud-Based InSAR Science project. These initiatives aim to simplify the use of SAR data, make it readily available, and prepare for the expected increase in SAR data volumes [90]. Upcoming missions like the NASA/Indian Space Research Organisation SAR mission (NISAR) are expected to generate vast amounts of data, necessitating innovations in data hosting and processing. These projects are focused on cloud-based processing and data sharing, which will allow global teams to collaborate more effectively using the internet, improving the accessibility of this data around the world [91].

As part of these initiatives, improved utilities for data discovery, access, and processing are being developed. This includes the creation of products like the ARIA Sentinel-1 Geocoded Unwrapped Interferogram (ARIA-S1-GUNW), which is now one of the largest publicly available InSAR archives [92]. Furthermore, the EO-ALERT initiative is aimed at developing a cutting-edge data processing system. This involves shifting crucial EO data processing components from ground-based systems to the satellite itself, ensuring rapid delivery of data products directly to users. The goal is to achieve significantly faster data transfer and processing, essentially providing near-instantaneous access to EO data. Within the scope of EO-ALERT, the Inter-satellite Data Relay System (IDRS) service emerges as a highly effective solution for globally distributing products processed on-board, achieving this in a matter of seconds [93]. One of the case studies proposed for this mission is the Extreme Weather Scenario. Designed to forecast convective storms rapidly through on-board analysis of EO satellite imagery, using ML techniques. This methodology has shown promising results in both feasibility and practical application for short-term storm prediction. The system, which involves the identification, tracking, and feature extraction of potential storm cells, followed by ML-based classification, has demonstrated effective outcomes. These are evident in both qualitative assessments (comparison with the RDT-CW product [94]) and quantitative evaluations (verification scores) [93]. The EO-ALERT project's effectiveness in on-board data processing and communication for a second use case, specifically ship detection, has been confirmed through analogous tests. Anticipated advancements in the system's ability to accurately identify targets are expected with the refinement of its models. Additionally, given the growing availability of appropriate on-board processing technology, the exploration and potential integration of DL algorithms are underway, which will lead to further enhancements in performance.

Currently, efforts are also being directed toward incorporating the detection of Overshooting Tops using data from SEVIRI's High-Resolution Visible (HRV) channel [93].

Capella Space launched an Open Data Program making data available for research and development in areas like computer vision and ML, marking a significant step in making SAR data widely accessible. The program aims to provide ultra-high resolution, low-latency SAR data directly to researchers, nonprofits, developers, and disaster response organizations, in an attempt to democratize access to high-resolution SAR data [95]. Accessing SAR data through Capella's Open Data Program is straightforward. Users can access the data collection through the Capella Console, which allows for the analysis of high-resolution SAR data and its integration into various applications [96].

From November of 2023, Umbra offers its SAR data through the platform "SkyFi's" (a renowned geospatial hub) marking a significant step in making SAR data more accessible by integrating Umbra's open data and archives into the SkyFi platform. Users can access now over 10,000 high-resolution SAR images from Umbra's archive, along with daily updates that include over 200 new collections each week. The platform provides global coverage with time-series SAR data from over 20 locations at no cost. This strategic partnership aims to democratize access to SAR data, catering to a broad audience ranging from experts to beginners. It enables comprehensive Earth monitoring capabilities across various domains such as environmental conservation, urban development, and infrastructure management. The integration enriches SkyFi's offerings, combining the ability to task Umbra's constellation with direct access to a rich repository of open and archived SAR data, all within a single, user-friendly platform [97].

B. Algorithms adaptability

SAR systems operate in dynamic environments where conditions such as weather and target variability can significantly change. To address this, adaptable algorithms can be employed, capable of adjusting their complexity and parameters in real-time, optimizing resource usage, and maintaining performance under varying conditions. Moreover, SAR systems, known for generating large data volumes, benefit from adaptable compression (such as BAQ [32]) and feature extraction algorithms that help reduce data volume [98], thereby facilitating efficient data transmission to ground stations. Advanced SAR systems also require a degree of autonomy to enable real-time decisions regarding data processing, mode switching, and resource allocation. Integrating ML algorithms further enhances system adaptability, allowing it to learn from new data and adapt to different environments, an essential capability for autonomous operation in changing and challenging conditions. Hence the need for adaptive algorithms that take into account the variability of SAR data and the variability of uses and scenarios for it.

Unibap, a Sweden-based computer system technology developer [99], aligns well with these needs through its innovative SpaceCloud system. SpaceCloud is a payload computing hardware system complemented by a software framework that enables on-orbit cloud edge computing, as well as data processing, storage, and analytics. This technology is designed to support advanced automation systems in space and intelligent vision solutions on Earth, showcasing Unibap's commitment to enhancing automation and AI capabilities in various industries [100]. Unibap's SpaceCloud aims to revolutionize the space industry by accelerating the adoption of on-board data processing capabilities, making them more accessible globally. This is particularly significant for satellite development teams, offering them enhanced flexibility and adaptability in satellite operations [101]. Unibap's agreement with ESA to demonstrate SpaceCloud in orbit is a pivotal step in this direction. The system investigates software-defined satellite concepts, allowing for operational modifications in orbiting systems to achieve new objectives.

A landmark achievement for Unibap was the successful reconfiguration of a sensor on an operational satellite in December 2021. This involved redesigning a solution in just three weeks, retraining the satellite's neural network with new inputs from the ground, altering operating algorithms, and acquiring and downlinking new data. This mission showcased the potential for more versatile satellites using current hardware and subsystem setups [101].

The Frontier Development Lab (FDL) program, working in partnership with ESA, has made notable advancements in the domain of Cognitive Cloud Computing in Space (3CS). These advancements were demonstrated in experiments on a D-Orbit InOrbit NOW (ION) satellite carrier mission. The FDL's ML payload showcased its ability to reduce downlink latency, adapt to various optical instruments, and receive updates directly in space. This enabled quick information extraction and delivery to end users. Furthermore, FDL developed an ML payload for hosting third-party applications, launched on a D-Orbit mission in January 2023 [102].

ESA's significant focus on 3CS includes funding 12 projects related to this concept and co-funding activities like the AI-express (AIX) [103] being developed by Planetek [104], D-Orbit [105], and AIKO [106]. The FDL's NIO (Networked Intelligence in Orbit) experiments, supported by ESA ϕ-lab, centered around the WorldFloods ML payload. This payload, developed in 2019 and published in Nature, was launched on the D-Orbit ION Wild Ride mission and operates on D-Orbit's Nebula cloud environment alongside Unibap's SpaceCloud computer. The WorldFloods payload [107] demonstrated its ability to process pre-loaded Sentinel-2 flood images, converting pixel data to bounded polygons of flood areas, resulting in a 10,000-fold reduction in data packet size. This processed data was rapidly downlinked and found to perform comparably with conventionally produced flood maps. The payload was also successfully adapted to images from the onboard RGB D-Sense camera and generated accurate vector maps of waterbodies, land, and clouds within 36 seconds. Additionally, FDL achieved the deployment of an updated ML payload in orbit, demonstrating the feasibility of uploading new model parameters to onboard processors, crucial for future 3CS infrastructure. These experiments highlight the potential of 3CS, suggesting how spacecraft with in-orbit cloud infrastructure can revolutionize disaster response, emissions management, weather forecasting, and space situational awareness. A subsequent ESA-funded mission, Dashing Through the Stars, includes a miniaturized hyperspectral camera by VTT, allowing third parties to run DL models for onboard processing, opening new avenues for software-defined missions in EO [102].

By adapting to new mission criteria and responding to changing environmental conditions, SpaceCloud exemplifies the kind of adaptable technology crucial for SAR systems, enhancing their functionality and application in space exploration and EO [108].

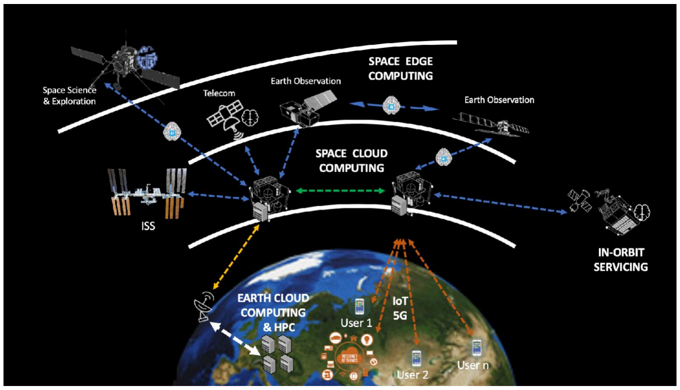

Fig. 5: Space Cloud Computing provides a scalable and elastic platform for running applications in space. This can help to reduce costs and complexity and enable new and innovative applications such as in-orbit servicing, IoT, and 5G [114].

V. Image-driven vs Information-driven approach

As the demand for SAR data grows, there is a need to evolve the way it is processed and provided to end-users, especially companies. The traditional approach to SAR focuses primarily on capturing and processing raw radar data to create detailed images of the Earth's surface. This process typically involves capturing raw data, compressing it, and then transmitting it to a ground station where further processing and analysis occur. However, the integration of cognitive cloud computing in space enhances this traditional approach by adding advanced on-board processing capabilities that enable the extraction of specific information directly from the SAR data while still in orbit. The diagram in Fig. 6 illustrates the shift in paradigm from traditional SAR systems to the advanced approach that combines the traditional technique with cognitive SAR (C-SAR) [109], [110]. Traditional SAR provides a detailed image of an area, requiring analysts to manually identify and extract features of specific targets while incorporating the C-SAR segment enabling the rapid delivery of detailed information about specific target features, such as location coordinates or displacement, thereby simplifying the analysis process. Moreover, this approach significantly reduces the volume of data that needs to be downlinked to just a few kilobytes. This smaller data size is more manageable and can be transmitted more efficiently, allowing the information to potentially reach the end user almost instantaneously.

On-board SAR processing technologies like adaptive beam steering [111], spotlight mode operation [112], and automated data product generation [113], greatly enhance the satellite's capability to acquire and process vital information without reliance on ground-based tasking or manual scheduling. These advancements contribute to more responsive and efficient SAR missions, particularly valuable in situations requiring rapid data analysis and dissemination, hence data can be delivered to end-users more efficiently.

In the context of SAR on-board processing, the terminologies 'image-driven' and 'information-driven' denote two distinct methodologies employed in the processing of SAR data, predominantly for the generation of SAR imagery or derivative products. Each methodology presents its unique benefits and complexities. A detailed examination of these two methodologies is provided below:

1) Image-Driven approach: In this approach, the entire raw SAR data (or a significant portion of it) is processed on-board to form a SAR image. After obtaining the image, further analysis, such as feature extraction or change detection, can be performed on the image itself. Through this approach, complete images are produced, providing a broad context for analysis, typically resulting in higher spatial resolution images. However, this requires significant on-board computational resources to handle the SAR image formation process, and the transmission of the complete image to the ground can be bandwidth-intensive.
   Algorithms like Range-Doppler Algorithm (RDA), Chirp Scaling Algorithm (CSA), and Omega-K Algorithm (ωKA) are commonly used. These algorithms are computationally expensive due to the need for complex mathematical operations such as Fast Fourier Transforms (FFTs), convolution, and interpolation [41]. The RDA involves operations in both range and Doppler domains, requiring multiple FFTs and data matrix manipulations [115]. The CSA, however, is used for focusing SAR data in the spectral domain and can be computationally intensive due to its scaling operations and additional FFTs for chirp compression, although it was created to avoid the interpolation in the range cell migration correction step in RDA [41]. The Omega-K Algorithm is also resource-intensive, particularly for wide-swath SAR imaging, due to its need for 2D interpolation and complex spectral domain processing [116]. These algorithms contribute to the high computational load during the SAR image formation process, demanding robust on-board processing capabilities. Additionally, the processing time and resources required increase with the desired resolution and size of the SAR image, making this approach challenging for real-time applications and satellites with limited processing capabilities.
2) Information-Driven approach: Current SAR missions are dependent on a limited number of specialized ground stations that receive large volumes of SAR data, typically ranging from 20 to 40 GB per transmission. Often, the final useful information extracted from this data, like ship coordinates or wind vector fields, is only a few kilobytes in size. The delay in processing this information can be significantly reduced by shifting SAR data processing to the spacecraft itself, followed by the immediate transmission of the processed data through low bandwidth communication channels [78]. Moreover, an additional advantage of processing SAR data on-board is the capability for the spacecraft to autonomously make decisions, such as adjusting instruments based on the latest information derived from the processed SAR images. Instead of forming a full-fidelity image, the raw SAR data is directly processed on-board

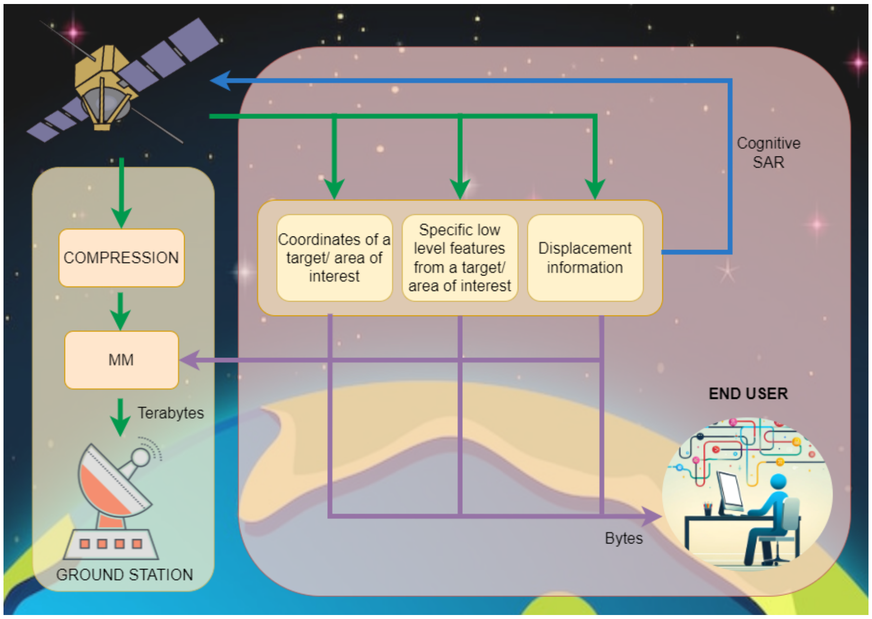

Fig. 6: Traditional SAR approach complemented by cognitive SAR with an example of three independent applications running in parallel. This type of architecture is applicable also to institutional missions like Copernicus.

to extract specific information or features of interest. This is especially useful for tasks such as ship detection, moving target indication, or anomaly detection. In this case, only the extracted information, such as the location of detected objects or wind vector fields would be sent to the ground, reducing the data downlinked to a few kilobytes [78]. The information-driven approach results in efficient use of the bandwidth, due to only the final products being transmitted to the ground station, making the system computationally more efficient, as only a subset of the data is required to produce the desired information product.

In institutional EO missions, the focus is to create a comprehensive reference database, which then is made available to the general public. In contrast, established space industry stakeholders prioritize the final product and may or may not adopt the entire L0-L1-L2 framework based on its suitability and cost-effectiveness for their specific needs.

By shifting away from viewing SAR data primarily as a tool for EO, we open the door to an array of potential applications. Rather than focusing on refining data for a visual representation, crucial information can be directly extracted from the raw data. This information can range from geographical information to dynamic changes occurring on the Earth's surface. For example, SAR data can detect minute alterations, such as a change in a power line's position or condition. Such real-time information is invaluable for end users; in the power line example, an immediate alert can prompt maintenance teams to inspect and rectify potential issues, ensuring an uninterrupted power supply and preventing larger infrastructural damages. Moreover, direct extraction of insight from data reduces the data volume. Instead of downlinking gigabytes of raw data, only a few essential bytes, encapsulating crucial information, are transmitted to the ground station or even directly to the end users. This allows for real-time, "satellite over-the-head" instantaneous applications. Innovative business models such as Constellation-as-a-Service, Satellite as a service (SaaS) and Insight as a service (IaaS) are gaining traction in the commercial EO market, replacing conventional product-centric business models. Definitions often exhibit overlaps, but in broad terms, Constellation-as-a-Service refers to a platform where the constellation is provided as a service of data gathering. Servitized constellations may therefore be shared across multiple customers. Such a model often requires tight cooperation from the initial design stages between the customer and the service provider [117]. A compelling example of this model is provided by Satellogic, which offers a Constellation-as-a-Service to a diverse set of customers. Enabling on-demand satellite tasking over specific areas of interest, Satellogic reduces operational and technological for customers and enables access to the company's ground station network [118]. SaaS refers to the delivery of satellite data and services over the internet, similar to how cloud computing providers deliver software and infrastructure. Satellite operations and data collection are outsourced to a third-party service provider, which allows clients to access satellite capabilities without the need to own or operate their satellite systems, making satellite data more accessible and affordable. The satellite may also serve as a platform to run software applications provided by customers. The Key characteristics of SaaS that apply to SAR EO are:

- On-demand access: Users can access satellite data and services without having to own or operate

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satellites.
- Pay-as-you-go: Users only pay for the data and services they use, which can significantly reduce costs and force satellite operators to have multiple applications on the same mission.
- Scalability: Users should be able to easily scale their data requirements up or down as needed.

Examples of current SaaS providers can be seen in Planet Labs [119] or DigitalGlobe, acquired by Maxar Technologies [120], which sell satellite imagery and analytics for a variety of industries, including agriculture, forestry, and environmental monitoring. Furthermore, there is a broader trend of governments contracting commercial providers for EO capabilities, bypassing the cost and time associated with developing indigenous satellite systems. Different countries, including Japan, are showing interest in purchasing SAR data from Capella Space [121]. Indonesia, for example, has contracted Thales Alenia Space and BlackSky for a dedicated EO constellation combining radar and optical sensors [122]. In addition to providing data services, Capella is actively exploring opportunities to provide smallsats for the United Kingdom and the United Arab Emirates (and eventually other countries as well). Both countries aim to acquire satellites that can be independently operated and seamlessly integrated into their respective national space frameworks [121].

IaaS elevates the concept further by not just supplying data, but also offering valuable, actionable insights obtained from that data. This service involves the provision of cloud-based applications and platforms dedicated to processing, analyzing, and extracting meaningful information from satellite data. This allows users to focus on extracting value from their data without having to invest in specialized software or infrastructure. The key characteristic of IaaS, which can be seen as a higher value evolution of SaaS, is the focus on data processing and analytics on-demand: users can utilize IaaS platforms to process, analyze, and visualize satellite data, focusing on "actionable data products" only. IaaS providers offer tools for applying machine learning and artificial intelligence techniques to satellite data, enabling advanced analysis and predictive modeling via customizable dashboards and applications. Users can create bespoke dashboards and applications to visualize and share insights from their satellite data.

Examples of IaaS providers are very much linked to cloud providers:

- Google Earth Engine provides a cloud-based platform for analyzing and visualizing satellite imagery and data. They also provide over thirty years of historical imagery, with over 80 petabytes of geospatial data ready for analysis [123].
- Microsoft Azure IoT Hub offers a platform for ingesting, processing, and storing satellite data from IoT devices and sensors. The Azure Orbital Ground Station service enhances the speed of data processing by directly connecting downlinked data from satellites to Azure, allowing seamless use with other Azure services, like Azure Storage, Azure AI, and Azure Data Analytics. Moreover, it includes comprehensive security measures and compliance, ensuring the safety and privacy of data. The Azure Orbital Ground Station service facilitates the operation of space missions with the reliability and flexibility of cloud technology [124].
- Amazon Web Services (AWS) Elastic MapReduce (EMR) provides a service for running large-scale data processing jobs on satellite data [125].

This shift in perspective and approach is aptly termed the "information-driven" approach, instead of processing data for a general purpose, data is processed onboard with a specific product or end goal in mind. This further aligns with the aforementioned transition from a product-oriented approach focused on developing technologies for data creation, to a service-oriented one, tailored to specific applicative contexts and user needs. Some examples are:

- Disaster monitoring: SAR data can be used to detect flooding in real time. Once floodwaters start to rise, the system can immediately notify disaster management authorities, facilitating quicker evacuations and deployment of resources.
- Infrastructure monitoring: beyond power lines, SAR can monitor the structural health of bridges, dams, and buildings. Any subtle shift or deformation can be immediately detected, ensuring timely maintenance and preventing potential disasters.
- Environmental changes: SAR systems can detect illegal deforestation activities by spotting abrupt changes in forest cover. Conservation authorities can be alerted in real time, leading to swift action against the culprits.
- Maritime surveillance: changes in sea ice or the movement of large marine animals, like whales, can be tracked. For ships navigating polar regions, real-time ice mapping can be crucial. For conservationists, tracking animal movements aids in their protection.
- Agriculture: farmers can benefit from immediate information regarding soil moisture levels or pest infestations, helping them make timely decisions about irrigation or pesticide application.

Essentially, by transitioning to an information-driven approach, SAR systems can be tailored to cater to niche requirements, offering real-time solutions across diverse sectors. The potential of SAR systems thus expands manifold, revolutionizing how satellite data is used.

Advancements in technology make it possible to directly convert raw data (L0) into actionable data (L4) for immediate use by end-users, streamlining the data processing pipeline. This transition allows for more efficient and timely delivery of information. For example, a government space agency might launch an institutional

EO satellite to collect data for scientific research and environmental monitoring. In this case, the emphasis is on creating a comprehensive database (L2 or L3) of environmental parameters, which will be made available to researchers, educational institutions, and the general public. The end-users, in this scenario, are not dictating specific data processing requirements; the goal is to provide a valuable resource.

On the other hand, a commercial satellite operator focused on providing real-time weather forecasting data for emergency services and the aviation industry, recognizes the critical importance of low data latency. To meet the needs of time-sensitive applications, they aim to transition directly from raw data (L0) to actionable weather data (L4). In this context, the final product, which is actionable weather data with minimal processing delay, takes precedence.

This scenario underscores that for applications where timely access to data is vital, such as emergency response and aviation safety, low data latency becomes a driving factor in shaping the data processing strategy. In institutional EO missions, the focus is on creating a comprehensive reference database, and the data generated is made available to the public.

Some challenges derived from this approach are the need for different specific algorithms for different types of products, depending on the application, and the risk of discarding information that could be critical for a broader context. In other words, different applications need different products that can be derived from the same SAR data, by applying different algorithms and focusing on different information provided by the sensor.

The choice between an image-driven and an information-driven approach will depend on the specific requirements of the SAR mission, available on-board computational resources, transmission bandwidth, and the desired end products or information. As technology evolves, SAR satellites and airborne systems are increasingly incorporating both approaches to strike a balance between delivering high-resolution images and specific information products efficiently.

VI. Conclusion

This comprehensive review highlights the crucial transformation in SAR data processing, driven by the advancement of on-board processing techniques. By transcending traditional ground-based processing paradigms, these advancements are not just enhancing the immediacy and efficiency of remote sensing operations but are also paving the way for innovative cloud-based business models such as SaaS and Models as a Service (MaaS). These approaches aim to make satellite data more accessible to everyone, simplifying operational challenges and removing the necessity for individuals or entities to own satellites directly.

The integration of cutting-edge technologies, including AI, ML, and cloud computing, with SAR systems, is marking the beginning of a new phase in space-based surveillance. These technologies are instrumental in overcoming long-standing challenges related to data volume management, transmission bandwidth constraints, and the urgent need for data accessibility. Moreover, the development of robust processing units and the implementation of ”SpaceCloud” concepts are redefining data processing and management in orbit, offering scalable and adaptable solutions for real-time SAR data analysis.

The shift towards on-board processing is facilitating a broad spectrum of EO missions and constellations, significantly impacting areas such as environmental monitoring, disaster management, and global security. Through enhanced real-time processing capabilities, SAR systems are capable of delivering critical data for fire detection, rogue ship tracking, and surveillance of environmental hazards with unprecedented speed and efficiency.

Looking forward, the potential of Copernicus data as a cornerstone for scientific and commercial applications signifies the growing relevance of SAR data in advancing Earth sciences and operational applications. The envisioned extension of missions within the Copernicus framework, such as Cognitive SAR, highlights the evolving landscape of space-based EO and the growing symbiosis between traditional institutional missions and commercial initiatives.

In summary, the advancement of on-board SAR data processing technologies signifies important progress in the field of remote sensing, creating new avenues to boost the effectiveness and operational efficiency of satellite networks. As we progress through this transformative phase, the blend of AI, ML, and cloud computing with SAR technologies offers a promising area for ongoing research and innovation, aiming to elevate the functionalities of SAR missions and extend the reach of EO further.

Appendix

Table: SAR Missions, Data Handling, and Technological Advancements

TABLE III: SAR Missions, Data Handling, and Technological Advancements

On-board Processing Benefits	Reduces latency, improves bandwidth efficiency and enables adaptive mission planning.
Challenges	Limited storage capacity and downlink availability pose significant limitations on the sensor's acquisition duty cycle, especially for smaller platforms.
Downlink Improvements	Recent advances include the use of Ka-band for over 1 Gbps downlink rates and explorations toward the adoption of optical downlink technologies.
Current Bottleneck	Managing increased azimuth resolution and swath width, which significantly augment the volume of raw data generated, necessitating more sophisticated on-board processing capabilities.
Mission/Data	- **ERS-1 and ERS-2**: C-band, 2300 kg mass, 105 Mbps, no on-board storage. Launched in July 1991 and April 1995 respectively. - **Envisat**: C-band, 8255 kg mass. Advanced SAR (ASAR), LBR $<$ 4.6 Mbps, MERIS + LBR $<$ 50 Mbps, HR 100 Mbps. Resolution over ocean: 1040 m x 1200 m, land: 260 m x 300 m. Launched in March 2002. - **TerraSAR-X and TanDEM-X**: X-band, 1250 kg and 525 kg mass respectively. Resolution of 2 x 1 m or 1 m x 1 m depending on the mode, for TerraSAR-X. TanDEM-X resolution varies from 1.2 m x 1-4 m, 3 m x 3-6 m, and 16 m x 16 m depending on the mode. Applications such as topography and DEM maps. Launched in June 2007 and June 2010 respectively. - **COSMO-SkyMed**: X-band, 1700 kg mass, resolution between 3 and 5 m. Applications such as environmental monitoring and disaster relief. Launched in June 2007. - **Sentinel-1 A and B**: 90 GB/orbit, 2300 kg mass. Depending on the mode the resolution varies from 5-by-5 m to 5 m x 20 m. Level 0 products within 3 hours, Level 1 within a day. Launched in April 2014, and in April 2016 respectively. - **ALOS-2**: L-band, 2100 kg mass. Resolution of 1 m in azimuth by 3 m in range. Applications such as cartography, regional observation, and disaster monitoring. Launched in May 2014. - **Gaofen-3**: C-band, 2279 kg mass. The spatial resolution ranges from 1 m to 500 m. Applications such as cartography, regional observation, and disaster monitoring. Launched in August 2016. - **NovaSAR-1**: S-band with a mass of 430 kg and a resolution of 6 m. Its applications range from crop type classification to crop condition and moisture content. Launched in September 2018. - **Denali (Capella-1)**: X-band with a mass of less than 40 kg and a resolution of 0.5m, for all-weather imagery using origami-like antenna [126]. Launched in December 2018. - **RADARSAT Constellation**: C-band, 2,200-2,750 kg of mass per satellite, with a spatial resolution of 1 m -100 m. Launched in June 2019. - **SAOCOM**: L-band, with a mass of 3,050 kg. The spatial resolution varies depending on the mode: 10 m x 50 m, 10 m x 30 m, and 10 m x 100 m. The applications are agriculture, fishery, and forestry, among others. Launched in August 2020. - **Sequoia (Capella-2)**: X-band, with a mass of 112 kg [127]. The spatial resolution varies depending on the mode: 0.25 m azimuth for a swath of 5 x 5 km, 0.5 m for 10 km, and 1.2 m up to 100 km x 10 km [128]. Part of a plan to build the smallest commercial radar satellites in the world [129]. Launched in August 2020. - **Whitney Constellation (Capella-3, ..., 10)**: X-band with a mass of around 110 kg. Resolution of 0.5 m for applications such as mapping, surveillance, and monitoring, allowing for the detection of small targets [129]. Launched from 2021 to 2023. - **Umbra-SAR 2001**: X-band microsatellite, with a mass of 65 kg. It offers a resolution of 25 cm [130]. Launched on June 2021. - **Umbra-02, ..., 08**: Launched throughout 2022-2023, X-band microsatellites, with a mass of 65 kg. They offer high resolution, down to 25 cm [131]. Launched from 2021 to 2023. - **Acadia (Capella-11+)**: X-band, with a mass of less than 197 kg. The increase in bandwidth compared to the older Capella satellites generations, from 500 MHz to 700 MHz, will lead to an improvement in resolution, which will reach a slant range resolution of 0.214 m, and a ground range resolution of 0.31 m [132]. Launched in August 2023. - **Future Missions**: e.g., ROSE-L with significantly higher data volumes, L-band, and a spatial resolution of 5-10 m, for geohazard monitoring.
Compression	- Essential for storage efficiency and handling communication interruptions. - **Adaptive Sampling**: Block Adaptive Quantization (BAQ) for selective data retention, real-time area of interest identification, and algorithmic implementation using ML. - Reduces bandwidth, ensuring quicker and cost-effective data transmission.
Technological Advancements	- **Hardware Improvements**: FPGAs, MPSoC Technologies, Reconfigurable Accelerators, use of COTS components for enhanced on-board processing efficiency and speed. - **High-Speed Communications**: The use of Ka-band for over 1 Gbps downlink rates. Data Highway for data transfer up to 1.8 Gbit/s, enabling rapid relay of LEO satellite data. - **On-Board Processing Challenges**: Limitations include processing power, latency, revisit time, and the balance between data compression and integrity. - **SWaP-C Limitations**: Emphasizes the need for effective compression algorithms to manage the size, weight, power, and cost constraints.

REFERENCES

[1] J. C. Curlander and R. N. McDonough, *Synthetic aperture radar*. Wiley, New York, 1991, vol. 11.

[2] C. Elachi, "Spaceborne radar remote sensing: applications and techniques," *New York*, 1988.

[3] A. G. Castriotta, "Copernicus sentinel data access annual report 2022," Serco Spa," Issue 1 Rev 0, 2023. [Online]. Available: https://sentinels.copernicus.eu/documents/d/sentinel/cope-serco-rp-23-1493_sentineldataaccessannual_report_2022

[4] A. Moreira, P. Prats-Iraola, M. Younis, G. Krieger, I. Hajnsek, and K. P. Papathanassiou, "A tutorial on synthetic aperture radar," *IEEE Geoscience and remote sensing magazine*, vol. 1, no. 1, pp. 6–43, 2013.

[5] S. N. Madsen and H. A. Zebker, "Imaging radar interferometry," *Manual of remote sensing*, vol. 2, pp. 349–380, 1998.

[6] G. Krieger, A. Moreira, H. Fiedler, I. Hajnsek, M. Werner, M. Younis, and M. Zink, "Tandem-x: A satellite formation for high-resolution sar interferometry," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 45, no. 11, pp. 3317–3341, 2007.

[7] X. Xu, X. Zhang, and T. Zhang, "Lite-yolov5: A lightweight deep learning detector for on-board ship detection in large-scene sentinel-1 sar images," *Remote Sensing*, vol. 14, no. 4, 2022. [Online]. Available: https://www.mdpi.com/2072-4292/14/4/1018

[8] Space Economy Observatory, "Space Economy: la nuova frontiera dell'innovazione si presenta!" 2020. [Online]. Available: https://www.osservatori.net/it/prodotti/formato/infografiche/space-economy-nuova-frontiera-innovazione-si-presenta-infografica

[9] J. Li, J. Chen, P. Cheng, Z. Yu, L. Yu, and C. Chi, "A survey on deep-learning-based real-time sar ship detection," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 16, pp. 3218–3247, 2023.

[10] National Oceanic and Atmospheric Administration, "Search and rescue satellites - geosar satellites," https://www.sarsat.noaa.gov/search-and-rescue-satellites/, 2024, accessed: 2024-03-28.

[11] W. Tian, C. Hu, T. Zeng, and Z. Ding, "Several special issues in geo sar system," in *8th European Conference on Synthetic Aperture Radar*, 2010, pp. 1–4.

[12] eoPortal, "Copernicus: Sentinel-1." [Online]. Available: https://www.eoportal.org/satellite-missions/copernicus-sentinel-1

[13] Spaceflight101, "Alos-2 – spacecraft & satellites," https://spaceflight101.com/spacecraft/alos-2/.

[14] EO Portal, "Saocom (sar observation & communications satellite)," https://www.eoportal.org/satellite-missions/saocom#performance-specifications, 2023.

[15] A. Moreira, P. Prats-Iraola, M. Younis, G. Krieger, I. Hajnsek, and K. P. Papathanassiou, "A tutorial on synthetic aperture radar," *IEEE Geoscience and Remote Sensing Magazine*, vol. 1, no. 1, pp. 6–43, 2013.

[16] D. Geudtner, N. Gebert, M. Davidson, D. Petrolati, L. Iannini, S. Osborne, and R. Furnell, "Copernicus rose-l sar mission," in *EUSAR 2022; 14th European Conference on Synthetic Aperture Radar*, 2022, pp. 1–4.

[17] F. Wallrapp, R. Ballweg, and Y. Gataullin, "The european data relay system (edrs): Operational challenges," 10 2011.

[18] P. Snoeij, E. Attema, A. Monti-Guarnieri, and F. Rocca, "Gmes sentinel-1 fdbaq performance analysis," 06 2009, pp. 1 – 6.

[19] M. Zimmermanns and C. Roemer, "Copernicus hpcm: Rose-l sar instrument and performance overview," in *EUSAR 2022; 14th European Conference on Synthetic Aperture Radar*, 2022, pp. 1–6.

[20] Spaceflight101, "Sentinel-1 spacecraft overview." [Online]. Available: https://spaceflight101.com/copernicus/sentinel-1/

[21] European Space Agency, "SAR ERS Overview," https://earth.esa.int/eogateway/instruments/sar-ers/description.

[22] ESA, "Envisat Overview," https://earth.esa.int/eogateway/missions/envisat/description, 2023.

[23] German Aerospace Center (DLR), "Terrasar-x: Mission and system design," https://www.dlr.de/Portaldata/1/Resources/forschung_und_entwicklung/missionen/terrasar_x/EUSAR-TX-Mission.pdf, 2007.

[24] German Aerospace Center (DLR) and Airbus Defence and Space, "Tdx (tandem-x) - satellite missions," https://www.eoportal.org/satellite-missions/tandem-x, 2016.

[25] German Aerospace Center (DLR), "Tandem-x - a new high resolution interferometric sar mission," https://www.dlr.de/hr/en/desktopdefault.aspx/tabid-2317/3669_read-5488/, 2024.

[26] Umbra, "Umbra unveils bistatic sar data from its tandem pair of satellites," https://www.prnewswire.com/news-releases/umbra-unveils-bistatic-sar-data-from-its-tandem-pair-of-satellites-302082434.html, 2024.

[27] "Cosmo-skymed mission and products description," Italian Space Agency (ASI), Rome, Italy, Tech. Rep., 2019. [Online]. Available: https://www.asi.it/wp-content/uploads/2019/08/COSMO-SkyMed-Mission-and-Products-Description_rev3-1.pdf

[28] European Space Agency, "Radarsat-1 standard beam sar images," NAtional Snow and Ice Data Center, 1999. [Online]. Available: https://nsidc.org/sites/default/files/r1stanprod.pdf

[29] Center for Earth Observation , "Novasar-1 user guide," https://research.csiro.au/cceo/novasar/novasar-introduction/novasar-1-user-guide/.

[30] D. Steenari, K. Hoeflinger, M. Albinet, and T. Gärtner, "European workshop on on-board data processing (obdp2019)," Erasmus (European Space Research and Technology Centre (ESTEC)), Europe/Amsterdam, Feb 2019, organized by ESA.

[31] M. A. Richards, J. Scheer, W. A. Holm, and W. L. Melvin, "Principles of modern radar," 2010.

[32] C. Hay, L. Donnell, C. Crawshaw, M. Ireland, and M. Yaghoobi, "Adaptive on-board signal compression for sar using machine learning methods," 2023.

[33] H. Breit, S. Wiehle, S. R. Mandapati, D. Günzel, and U. Balss, "Demonstrating a sar satellite onboard processing chain," 2022.

[34] E. S. Agency, "International charter space and major disasters," 2023. [Online]. Available: https://www.esa.int/Applications/Observing_the_Earth/International_Charter_Space_and_Major_Disasters

[35] INVAP, "Dossier saocom 1a," https://saocom.invap.com.ar/wp-content/uploads/2018/10/Dossier-SAOCOM-1A-english.pdf, 2018.

[36] D. Mota, H. Cruz, P. R. Miranda, R. P. Duarte, J. T. de Sousa, H. C. Neto, and M. P. Véstias, "Onboard processing of synthetic aperture radar backprojection algorithm in fpga," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 3600–3611, 2022.

[37] C. Pieterse, W. P. du Plessis, and R. W. Focke, "Metrics to evaluate compression algorithms for raw sar data," *IET Radar, Sonar & Navigation*, vol. 13, no. 3, pp. 333–346, 2019.

[38] C. E. Shannon, "A mathematical theory of communication," *The Bell system technical journal*, vol. 27, no. 3, pp. 379–423, 1948.

[39] P. D. Grünwald, P. M. Vitányi, *et al.*, "Algorithmic information theory," *Handbook of the Philosophy of Information*, pp. 281–320, 2008.

[40] D. Cerra, A. Mallet, L. Gueguen, and M. Datcu, "Algorithmic information theory-based analysis of earth observation images: An assessment," *IEEE Geoscience and Remote Sensing Letters*, vol. 7, no. 1, pp. 8–12, 2009.

[41] I. G. Cumming and F. H. Wong, "Digital processing of synthetic aperture radar data," *Artech house*, vol. 1, no. 3, pp. 108–110, 2005.

[42] U. Benz, K. Strodl, and A. Moreira, "A comparison of several algorithms for sar raw data compression," *IEEE Transactions on geoscience and remote sensing*, vol. 33, no. 5, pp. 1266–1276, 1995.

[43] European Space Agency, "Packet Encoding - Sentinel-1 SAR Technical Guide," https://sentinels.copernicus.eu/web/sentinel/technical-guides/sentinel-1-sar/products-algorithms/level-0-products/packet-encoding, 2023.

[44] J. Fischer, U. Benz, and A. Moreira, "Efficient sar raw data compression in frequency domain," vol. 4, 02 1999, pp. 2261 – 2263 vol.4.

[45] N. G. Kasapoğlu, N. S. Tezel, and B. Yazgan, "Sar raw data compression with dct-baq."

[46] N. Instruments, "Peak signal-to-noise ratio as an image quality metric," 2013.

[47] S. Jiao and W. Dong, "Sar image quality assessment based on ssim using textural feature," in *2013 Seventh international conference on image and graphics*. IEEE, 2013, pp. 281–286.

[48] K. Shenoy, "The effects of signal and image compression of sar data on change detection algorithms," 2007.

[49] D. Cerra and M. Datcu, "Expanding the algorithmic information theory frame for applications to earth observation," *Entropy*, vol. 15, no. 1, pp. 407–415, 2013. [Online]. Available: https://www.mdpi.com/1099-4300/15/1/407

[50] M. Nakajima, T. Watanabe, and H. Koga, "Compression-based semantic-sensitive image segmentation: Prdc-ssis," in *2012 IEEE International Geoscience and Remote Sensing Symposium*. IEEE, 2012, pp. 4303–4306.

[51] N. Agrawal and K. Venugopalan, "Back propagation neural network approach for sar raw data compression," in *MILCOM 2008-2008 IEEE Military Communications Conference*. IEEE, 2008, pp. 1–4.

[52] N. Gollin, M. Martone, G. Krieger, and P. Rizzoli, "Ai-based performance-optimized quantization for future sar systems," in *IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium*, 2023, pp. 1771–1774.

[53] G. Giuffrida, L. Fanucci, G. Meoni, M. Batič, L. Buckley, A. Dunne, C. Van Dijk, M. Esposito, J. Hefele, N. Vercruyssen, *et al.*, "The ϕ-sat-1 mission: The first on-board deep neural network demonstrator for satellite earth observation," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–14, 2021.

[54] P. Xu, Q. Li, B. Zhang, F. Wu, K. Zhao, X. Du, C. Yang, and R. Zhong, "On-board real-time ship detection in hisea-1 sar images based on cfar and lightweight deep learning," *Remote Sensing*, vol. 13, no. 10, 2021. [Online]. Available: https://www.mdpi.com/2072-4292/13/10/1995

[55] H. Lu, X. Duan, and Y. Chen, "Integration of low earth orbit satellites with terrestrial cloud-edge systems," in *2021 International Conference on Space-Air-Ground Computing (SAGC)*, 2021, pp. 167–168.

[56] J. Chen, H. Zhang, and Z. Xie, "Space-air-ground integrated network (sagin): A survey," *arXiv preprint arXiv:2307.14697*, 2023.

[57] Terrawatch Space Insights, "Edge computing for earth observation," https://newsletter.terrawatchspace.com/p/edge-computing-for-earth-observation, 2023.

[58] D. Romano, V. Mele, and M. Lapegna, "The challenge of onboard sar processing: A gpu opportunity," in *International Conference on Computational Science*. Springer, 2020, pp. 46–59.

[59] X. Li, H. Guo, K.-S. Chen, and X. Yang, *Advances in SAR Remote Sensing of Oceans*. CRC Press, 2018.

[60] A. da Silva Curiel, A. Cawthorne, and M. Sweeting, "Progress in small satellite technology for earth observation missions," in *Small Satellites for Earth Observation: Selected Proceedings of the 5th International Symposium of the International Academy of Astronautics, Berlin, April 4-8 2005*, 2005, p. 50.

[61] H. J. Kramer and A. P. Cracknell, "An overview of small satellites in remote sensing," *International journal of remote Sensing*, vol. 29, no. 15, pp. 4285–4337, 2008.

[62] S. Marcuccio, S. Ullo, M. Carminati, and O. Kanoun, "Smaller satellites, larger constellations: Trends and design issues for earth observation systems," *IEEE Aerospace and Electronic Systems Magazine*, vol. 34, no. 10, pp. 50–59, 2019.

[63] Z. Chen, N. Chen, C. Yang, and L. Di, "Cloud computing enabled web processing service for earth observation data processing," *IEEE journal of selected topics in applied earth observations and remote sensing*, vol. 5, no. 6, pp. 1637–1649, 2012.

[64] A. Tsokas, M. Rysz, P. M. Pardalos, and K. Dipple, "Sar data applications in earth observation: An overview," *Expert Systems with Applications*, vol. 205, p. 117342, 2022.

[65] G. Curzi, D. Modenini, and P. Tortora, "Large constellations of small satellites: A survey of near future challenges and missions," *Aerospace*, vol. 7, no. 9, p. 133, 2020.

[66] S.-Y. Tan, "Remote sensing applications and innovations via small satellite constellations," *Handbook of small satellites: technology, design, manufacture, applications, economics and regulation*, pp. 767–797, 2020.

[67] G. Furano, G. Meoni, A. Dunne, D. Moloney, V. Ferlet-Cavrois, A. Tavoularis, J. Byrne, L. Buckley, M. Psarakis, K.-O. Voss, *et al.*, "Towards the use of artificial intelligence on the edge in space systems: Challenges and opportunities," *IEEE Aerospace and Electronic Systems Magazine*, vol. 35, no. 12, pp. 44–56, 2020.

[68] M. Kerr, S. Tonetti, S. Cornara, J.-I. Bravo, R. Hinz, A. Latorre, F. Membibre, C. Solimini, S. Wiehle, H. Breit, *et al.*, "Eo-alert: A novel architecture for the next generation of earth observation satellites supporting rapid civil alert," 2020.

[69] Airbus, "Space data highway," Accessed 2023. [Online]. Available: https://www.airbus.com/en/defence/connectivity/space-data-highway

[70] S. W. Paek, S. Balasubramanian, S. Kim, and O. de Weck, "Small-satellite synthetic aperture radar for continuous global biospheric monitoring: A review," *Remote Sensing*, vol. 12, no. 16, 2020. [Online]. Available: https://www.mdpi.com/2072-4292/12/16/2546

[71] M. N. Sweeting, "Modern small satellites-changing the economics of space," *Proceedings of the IEEE*, vol. 106, no. 3, pp. 343–361, 2018.

[72] G. Lentaris, K. Maragos, I. Stratakos, L. Papadopoulos, O. Papanikolaou, D. Soudris, M. Lourakis, X. Zabulis, D. Gonzalez-Arjona, and G. Furano, "High-performance embedded computing in space: Evaluation of platforms for vision-based navigation," *Journal of Aerospace Information Systems*, vol. 15, no. 4, pp. 178–192, 2018.

[73] E. I. Baungarten-Leon, G. D. Martín-del Campo-Becerra, S. Ortega-Cisneros, M. Schlemon, J. Rivera, and A. Reigber, "Towards on-board sar processing with fpga accelerators and a pcie interface," *Electronics*, vol. 12, no. 12, 2023. [Online]. Available: https://www.mdpi.com/2079-9292/12/12/2558

[74] Ó. Lucía, E. Monmasson, D. Navarro, L. A. Barragán, I. Urriza, and J. I. Artigas, "Modern control architectures and implementation," *Control of Power Electronic Converters and Systems*, pp. 477–502, 2018.

[75] C. Lesnik, A. Kawalec, and P. Serafin, "A real time sar processor implementation with fpga," *WIT Trans. Model. Simul*, vol. 51, pp. 435–444, 2011.

[76] W. Wolf, A. A. Jerraya, and G. Martin, "Multiprocessor system-on-chip (mpsoc) technology," *IEEE transactions on computer-aided design of integrated circuits and systems*, vol. 27, no. 10, pp. 1701–1713, 2008.

[77] S. Wiehle, S. Mandapati, D. Günzel, H. Breit, and U. Balss, "Synthetic aperture radar image formation and processing on an mpsoc," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–14, 2022.

[78] H. Breit, S. Mandapati, and U. Balss, "An fpga/mpsoc based low latency onboard sar processor," in *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*. IEEE, 2021, pp. 5159–5162.

[79] C. Wang, W. Lou, L. Gong, L. Jin, L. Tan, Y. Hu, X. Li, and X. Zhou, "Reconfigurable hardware accelerators: Opportunities, trends, and challenges," 2017.

[80] W.-K. Su, R. Sivilotti, Y. Cho, D. Cohen, B. Bray, and D. Doerfler, "Scalable, network-connected, reconfigurable, hardware accelerators for an automatic-target-recognition application," Technical report, Myricom Inc., Arcadia, CA, Tech. Rep., 1998.

[81] R. F. Hodson, Y. Chen, J. E. Pandolf, K. Ling, K. T. Boomer, C. M. Green, J. A. Leitner, P. Majewicz, S. H. Gore, C. S. Faller, *et al.*, "Recommendations on use of commercial-off-the-shelf (cots) electrical, electronic, and electromechanical (eee) parts for nasa missions," Tech. Rep., 2020.

[82] R. F. Hodson, Y. Chen, J. E. Pandolf, K. Ling, K. T. Boomer, C. M. Green, J. A. Leitner, P. Majewicz, S. H. Gore, and C. S. Faller, "Recommendations on Use of Commercial-off-the-Shelf (COTS) Electrical, Electronic, and Electromechanical (EEE) Parts for NASA Missions - Phase II," Tech. Rep., 2020.

[83] S. Wang, S. Zhang, X. Huang, J. An, and L. Chang, "A highly efficient heterogeneous processor for sar imaging," *Sensors*, vol. 19, no. 15, 2019. [Online]. Available: https://www.mdpi.com/1424-8220/19/15/3409

[84] A. Moreira, "Real-time synthetic aperture radar (sar) processing with a new subaperture approach," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 30, no. 4, pp. 714–722, 1992.

[85] F. Zhang, G. Li, W. Li, W. Hu, and Y. Hu, "Accelerating spaceborne sar imaging using multiple cpu/gpu deep collaborative computing," *Sensors*, vol. 16, no. 4, p. 494, 2016.

[86] Y. Cao, S. Guo, S. Jiang, X. Zhou, X. Wang, Y. Luo, Z. Yu, Z. Zhang, and Y. Deng, "Parallel optimisation and implementation of a real-time back projection (bp) algorithm for sar based on fpga," *Sensors*, vol. 22, no. 6, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/6/2292

[87] Andrea Radius, "Use of ai for sar image classification on-board," 2023. [Online]. Available: https://philab.esa.int/usecases/use-of-ai-for-sar-image-classification-on-board/

[88] European Space Agency, "Iceye constellation: Mission capabilities," 2023. [Online]. Available: https://www.eoportal.org/satellite-missions/iceye-constellation#mission-capabilities

[89] IMARC Group, "Synthetic aperture radar market size, share, trends 2023-2028," https://www.imarcgroup.com/synthetic-aperture-radar-market, 2023.

[90] J. Blumenfeld, "Big data meet open science," https://www.earthdata.nasa.gov/learn/articles/insar-access-success-story, May 2023.

[91] J. Blumenfel, "Getting ready for nisar and for managing big data using the commercial cloud," https://www.earthdata.nasa.gov/learn/articles/getting-ready-for-nisar, 2021.

[92] Alaska Satellite Facility, "Aria sentinel-1 geocoded unwrapped interferograms," https://asf.alaska.edu/data-sets/derived-data-sets/sentinel-1-interferograms/, 2023.

[93] R. Hinz, "Machine learning workshop presentation," EO-ALERT Project, 2020, available online. [Online]. Available: http://eo-alert-h2020.eu/wp-content/uploads/2020/12/Machine-Learning-WS_Hinz.pdf

[94] NWCSAF, "Rapidly developing thunderstorms (rdt) product," NWCSAF, 2020, available online. [Online]. Available: https://www.nwcsaf.org/AemetWebContents/ReferenceSystem/GEO/HTMLContributions/RDT/Prod_RDT.htm

[95] D. Messier, "Capella space opens its sar data to the public," https://parabolicarc.com/2021/09/14/capella-space-opens-its-sar-data-to-the-public/, Sept. 2021.
[96] Capella Space, "Community," https://www.capellaspace.com/community/, 2023.
[97] SkyFi. (2023) Skyfi's newest integration with umbra – elevating sar data accessibility. [Online]. Available: https://www.skyfi.com/blog/skyfis-newest-integration-with-umbra
[98] T. Algra and L. Bierens, "Advanced on-board sar data compressor," 09 2006, pp. 3537 – 3540.
[99] Unibap, "Unibap," https://unibap.com/.
[100] Hywel Curtis, "Spotlight: on-board data processing for next-generation satellites – with unibap," https://blog.satsearch.co/2022-03-23-on-board-data-processing-with-unibap, 2022.
[101] Unibap, "This is Unibap," https://unibap.com/about-us/.
[102] European Space Agency PhiLab, "Esa explores cognitive computing in space with fdl breakthrough experiments," https://philab.esa.int/esa-explores-cognitive-computing-in-space-with-fdl-breakthrough-experiments/, 2023.
[103] European Space Agency (ESA), "Aix express," https://incubed.esa.int/portfolio/aix/, 2023.
[104] Planetek Italia, "Planetek italia: Geospatial value," 2023. [Online]. Available: https://www.planetek.it/
[105] D-Orbit, "D-orbit: Space logistics and orbital transportation services," 2023. [Online]. Available: https://www.dorbit.space/
[106] AIKO Space, "Aiko space: Autonomous space mission technologies," 2023. [Online]. Available: https://aikospace.com/
[107] G. Mateo-Garcia, J. Veitch-Michaelis, L. Smith, S. V. Oprea, G. Schumann, Y. Gal, A. G. Baydin, and D. Backes, "Towards global flood mapping onboard low cost satellites with machine learning," *Scientific reports*, vol. 11, no. 1, p. 7249, 2021.
[108] G. Mateo-García, J. Veitch-Michaelis, C. Purcell, N. Longepe, S. Reid, A. Anlind, F. Bruhn, J. Parr, and P. P. Mathieu, "In-orbit demonstration of a re-trainable machine learning payload for processing optical imagery," *Scientific Reports*, vol. 13, no. 1, p. 10391, 2023.
[109] J. R. Guerci, "Cognitive radar: A knowledge-aided fully adaptive approach," in *2010 IEEE Radar Conference*, 2010, pp. 1365–1370.
[110] J. R. Guerci, R. M. Guerci, M. Ranagaswamy, J. S. Bergin, and M. C. Wicks, "Cofar: Cognitive fully adaptive radar," in *2014 IEEE Radar Conference*, 2014, pp. 0984–0989.
[111] G. Benitz, "Adaptive beamforming for sar ambiguity rejection," 2004.
[112] F. Stambouli, M. Limbach, T. Rommel, and M. Younis, "A cognitive maritime sar concept for high altitude platforms," 09 2019.
[113] P. A. Rosen, S. Hensley, I. R. Joughin, F. K. Li, S. N. Madsen, E. Rodriguez, and R. M. Goldstein, "Synthetic aperture radar interferometry," *Proceedings of the IEEE*, vol. 88, no. 3, pp. 333–382, 2000.
[114] European Space Agency, "ESA-ECMWF Workshop- Machine Learning for Earth System Observation and Prediction," https://events.ecmwf.int/event/291/contributions/2786/attachments/1524/2754/Mon_Welcome_1030_Mathieu.pdf.
[115] R. K. Raney, "The delay/doppler radar altimeter," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 36, no. 5, pp. 1578–1588, 1998.
[116] C. V. Jakowatz, D. E. Wahl, P. H. Eichel, D. C. Ghiglia, and P. A. Thompson, *Spotlight-mode synthetic aperture radar: a signal processing approach: a signal processing approach*. Springer Science & Business Media, 2012.
[117] A. Hein and C. Bruce Rosete, "Space-as-a-service: A framework and taxonomy of-as-a-service concepts for space," in *International Astronautical Congress 2022*, 2022.
[118] Satellogic, "Constellation-as-a-Service," https://satellogic.com/products/constellation-as-a-service/, 2024.
[119] Planet Labs PBC, "Daily earth data to see change and make better decisions," https://www.planet.com, 2023.
[120] M. Technologies, "Maxar is a leading space technology and intelligence company," https://www.maxar.com/about, 2023.
[121] S. Erwin, "Capella space sets sights on international market for radar satellites," *SpaceNews*, 2024. [Online]. Available: https://spacenews.com/capella-space-sets-sights-on-international-market-for-radar-satellites/
[122] ——. Blacksky inks $50 million deal to supply imagery services and satellites to indonesia. [Online]. Available: https://spacenews.com/blacksky-inks-50-million-deal-to-supply-imagery-services-and-satellites-to-indonesia
[123] G. E. Engine, "Meet earth engine," https://earthengine.google.com/.
[124] Microsoft, "Azure orbital ground station," https://azure.microsoft.com/en-gb/products/orbital#:~:text=Rapidly%20ingest%20data%20from%20space,a%20satellite%20ground%20station%20service.
[125] D. Guide, "Amazon elastic mapreduce," https://s3.cn-north-1.amazonaws.com.cn/aws-dam-prod/china/pdf/emr-dg.pdf, 2010.
[126] G. D. Krebs, "Capella 1 (Capella Denali)," https://space.skyrocket.de/doc_sdat/capella-1.htm.
[127] ——, "Capella 2, ..., 10 (Sequoia, Whitney)," https://space.skyrocket.de/doc_sdat/capella-2.htm, retrieved March 27, 2024.
[128] EO Portal, "Capella Space X-Band Synthetic Aperture Radar: Mission Capabilities," https://www.eoportal.org/satellite-missions/capella-x-sar#mission-capabilities, 2024.
[129] ——, "Payloads on the Spaceflight SSO-A Rideshare Mission - Capella X-SAR," https://www.eoportal.org/satellite-missions/capella-x-sar#payloads-on-the-spaceflight-sso-a-rideshare-mission, 2024.
[130] G. D. Krebs, "Umbra-SAR 2001," https://space.skyrocket.de/doc_sdat/umbra-sar-2001.htm, 2024, retrieved March 27, 2024.
[131] World Meteorological Organization, "Satellite: UMBRA - Observing Systems Capability Analysis and Review Tool (OSCAR)," https://space.oscar.wmo.int/satellites/view/umbra, World Meteorological Organization, 2023.
[132] Capella Space. (2022) Capella Space Unveils Next Generation Satellite with Enhanced Imagery Capabilities and Communication Features. Accessed: March 27, 2024. [Online]. Available: https://www.capellaspace.com/capella-space-unveils-next-generation-satellite-with-enhanced-imagery-capabilities-and-communication-features/