ONBOARD HYPERSPECTRAL CLASSIFICATION ENABLES GEOREFERENCING

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ABSTRACT

The Norwegian University of Science and Technology (NTNU) has been building a system composed of multiple remote sensing agents for ocean observations. NTNU launched the first HYPerspectral Smallsat for Ocean observation (HYPSO-1) satellite on the 13^{th} of January 2022, adding a Hyperspectral Imager satellite to its disposal, while HYPSO-2 will be launched in 2024. However, due to the high dimensionality of the collected data, onboard processing has been introduced on the satellite to potentially deliver information in a more rapid and condensed manner. In this paper, the operational use of onboard classification will be explored, investigating how different algorithms can be applied for data reduction to potentially enable decision-making onboard the satellite such as the use of classified images for onboard georeferencing. The classification could be used to enable near real-time data latency cooperation between the satellite and the other agents, such as autonomous surface vehicles for in-situ measurements.

***Index Terms*—** Onboard processing, Autonomous Systems, Classification, Cubesats, Georeferencing, Autonomous surface vehicle

1. INTRODUCTION

The use of hyperspectral imagers has been growing in the last decade due to their high performance in providing detailed information to users in both spectral and spatial domains. Multiple Hyperspectal Imagers (HSIs) satellites have been launched, including several CubeSat missions. NTNU has its own operational satellite, the HYPSO-1 [1], and a new satellite, the HYPSO-2, is scheduled to be launched in 2024. The amount of data generated is high due to the spectral detail that the hyperspectral imagers provide; for this reason, processing algorithms can be used to reduce the data size of and to extrapolate useful information that can be employed for decision-making, either on-ground or onboard. NTNU employs a series of autonomous agents forming an *observational pyramid*, consisting of satellites, unmanned aerial vehicles, autonomous surface vehicles, and autonomous underwater vehicles, as is represented in fig. 1. The challenge is to make them cooperate and work together to provide multiple types of information to monitor a given target area.

In addition to the Hyperspectal Imaging (HSI) payload, the HYPSO-2 satellite will incorporate a flexible Software Defined Radio (SDR), which will potentially allow it to adapt a communication protocol to varying system requirements and environmental constraints [2]. The flexibility of the SDR could be exploited to transmit data from the HYPSO-2 satellite to other agents in the pyramid. In particular, a first integration between HYPSO-2 and autonomous surface vehicles (ASV) is the selected scope for this paper.

The concept of operations is explained in the following: A given phenomenon on the Earth's surface could be identified by HYPSO-2. The satellite may then pre-process the Hyperspectral image by means of compression, classification [3] and georeferencing, as the amount of data for the SDR link would need to be kept low. The automation of operations for the cooperation of HYPSO-2 and ASV requires the definition of imposed constraints to ensure that, for example, the ASV is directed to the right area, or that the measurement taken onboard is reliable and relevant. This requires that the information to be transmitted includes precise georeferencing as the measurements would not be controlled by a person prior to transmission to the next sensor agent. The ASV can then sample the same area to provide local and detailed information to be complemented with the satellite measurements. Whenever the output of each algorithm detects that the information taken by the satellite presents one or multiple errors (see Section 3), the image can be disregarded directly onboard and the process would be aborted, to avoid erroneous

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guidance of the ASV while freeing resources on the satellite. Contour-matching georeferencing has been studied in previous works [4] [5], however the application of these algorithm onboard CubeSats is a novel field. As CubeSats and lower cost-missions can suffer of less precise attitude determination and control of the spacecraft, the application of such algorithms can aid in enhancing georeferencing. Similarly, interest in automation of operations and cooperations between different satellites and agents has been growing due to technology developments in the last years and the advantages of a synergic approach [6] [7]. The goal of the work presented in this paper is to investigate the usability of different onboard processing algorithms to enable future integration between satellites and other sensor agents, in order to reduce the time between the first anomaly detection until the next agent can be guided to the target area.

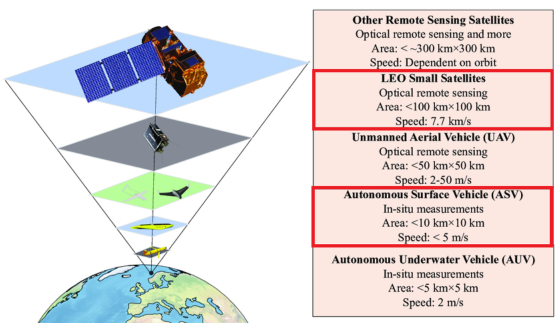
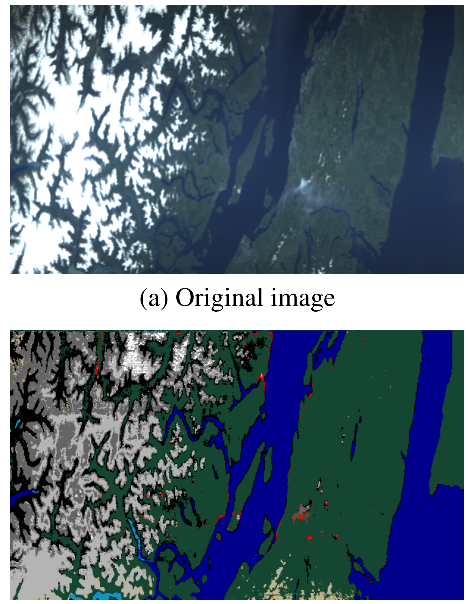


Fig. 1. Full *observational pyramid* for HYPSO [1]

2. ONBOARD CLASSIFICATION

Onboard classification consists of identifying the information represented by a defined number of physical features, such as land, sea, forest, urban areas, or algal blooms from the HSI cube. The algorithm has been tested on HYPSO-1 in June 2023, following the development of the method by Røysland [8]. In his work, Røysland implemented a machine learning algorithm, specifically a Support Vector Machine (SVM) with a Binary Decision Tree (BDT), to perform classification. Radiometric calibration is applied in order to take into account the light scene difference between different areas in the world, such as different sun angles and exposures. The onboard classification method selected employs Sparse Radiance calibration, which provides approximately 85% accuracy between the ground truth and predicted labels [8].

In the context of this work, the classified image has a dimension of 1092x598 pixels with a maximum number of classes equal to 16, encoded using 4 bits of data per pixel. The classification algorithm abates the data size with respect to lossless compression of the cube, from a maximum of 80 MB to 327 kB. This data reduction paves the way for more prompt and responsive operations of the satellite. Specifically, the classified image was downloaded from HYPSO-1 in 2.64 s [8], compared to an average of 10 min for a HSI cube, over an S-band radiolink.



(a) Original image

(b) Classified image

Fig. 2. Sechelt area in Canada on 6th June 2023

3. OPERATIONAL EVALUATION

In order to minimize the probability of sending wrong information to the ASV, several evaluations and constraints will be imposed onboard in order to discard information that can be misinterpreted. The data recorded by the satellite has to go through several checks in order to optimize the autonomous onboard decision-making; this allows the satellite to direct an ASV to a target area where a selected phenomenon has been observed. The evaluation and algorithms to be performed are:

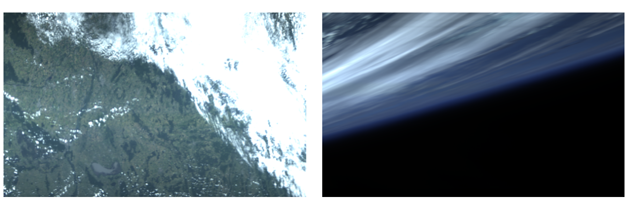
1. Compression ratio
2. Histogram statistics
3. Classification & Cloud cover evaluation
4. Georeferencing

3.1. Compression ratio

The hyperspectral processing on HYPSO-1 includes the lossless compression algorithm CCSDS-123 [1], which is run on the on-board FPGA for a standard cube size, or in the processing system for arbitrary cube sizes. In routine operations, a standard cube is composed of 1092x598 pixels and 120 spectral bands. CCSDS-123 is used for its simplicity, and for the considerable compression ratio which is of pivotal importance in the context of reducing the amount of data to be downloaded thus reducing energy spent for communications or increasing the number of potential captures per day. Birkeland et al. [9] investigated the possible relationship between the compression ratio and the image quality. The compression ratio *r* was defined as the compressed file size divided by the original size of the image. The evaluation of this figure of merit potentially allows the discarding of images presenting saturated pixels due to cloud cover and/or pointing errors. A threshold on *r* can be imposed to automatize operations by considering only more significant data.

3.2. Histogram statistics

A histogram shows the distribution of the intensities in an image per intensity. Counting the amount of overexposed or underexposed pixels, meaning pixels with intensity that is higher than an overexposure threshold or lower than an underexposure threshold, can give a more accurate degree of cloud cover, or indicate a pointing error where the HSI was pointing off the horizon of the earth and containing many dark pixels. The number of overexposed and underexposed pixels in an image is an indicator of the quality of an image and a threshold on them can be used for onboard decision-making with regards to further processing and communication with other agents.



(a) Partly cloudy (b) Pointing error

Fig. 3. Example scenes for the data in table 1

Scene	overexposed	underexposed	rest
(a)	30.24%	0.0 %	69.76%
(b)	1.21%	43.22%	55.56%

Table 1. Example histogram statistics that can be used for onboard decision-making

3.3. Classification & Cloud cover

The classification algorithm developed by Røysland [8] identifies a prescribed list of classes representing physical quantities; two of these classes represent *thick* and *thin clouds*. Even though cloud cover has been taken into consideration in the compression ratio and histogram evaluation, an assessment of absence or presence of the two classes allows us to directly evaluate if an image has limited use, and can therefore be deleted. By performing the compression ratio, histogram, and cloud cover check, it would be possible to identify most of the cloudy or failed pointing pictures [9].

3.4. Georeferencing

Georeferencing refers to the process of associating the image taken from a satellite to geographical coordinates with respect to each pixel. Many reliable algorithms have been applied to this problem, such as scale-invariant feature transform (SIFT) based feature mapping [10]. However, the SIFT algorithm is complex to run onboard the satellite, and other options must be sought. Bjørnsen [11] has adapted and tested an onboard direct georeferencing method for HYPSO-1 which takes as input the position and attitude of the satellite to associate latitude and longitude to the pixels of the image. This has been tested in a FlatSat on the ground, but the implementation to HYPSO-1, and possibly HYPSO-2, is straightforward. However, the method implemented presents some offset in georeferencing caused by inaccuracies in attitude and position measurements [11], as shown in fig. 4(a). As the satellite platform has been purchased by NTNU, these uncertainties may be neither easy to be identified nor under NTNU control.

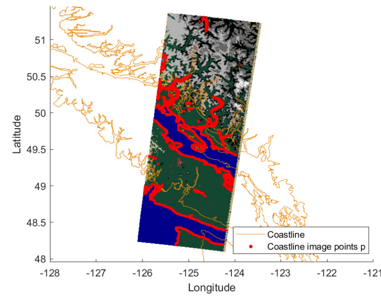
In the case of measurement targets in coastal areas, an indirect georeferencing method could then be applied to georeference the coastline present in an image. The method is based on the Iterative Closest Point approach [12], which is an algorithm that can be applied to find a match between 2D or 3D clouds of points. In the scope of this paper, the longitude and latitude of coastlines are the two dimensions to be matched, leading to a two-dimensional problem. Using the Røysland classification algorithm, the coastline can be easily identified, and then broadly georeferenced with the direct method developed by Bjørnsen [11]. Then, the pixels identifying the coastline can be compared to a database containing refined coastal points with exact longitude and latitude. If a match between the two is found, a precise georeferenced image is obtained.

The Iterative Closest Point can be applied to a directly georeferenced and classified image. In this work, the algorithm used is developed by Kroon [13]. After the identification of the latitude and longitude of the coastline in the image, the points are compared with the geographical coordinates available in the database, representing the ground truth. The algorithm solves the general problem of finding the rotation matrix R and the translation vector T to match the latitude and longitude of the image p, to the latitude and longitude of a database of coastlines as follows:

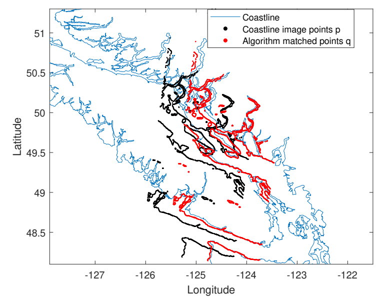
$$q = R * p + T. \tag{1}$$

The algorithm minimizes the distance by iteratively computing the rotation matrix R and the translation vector T for the

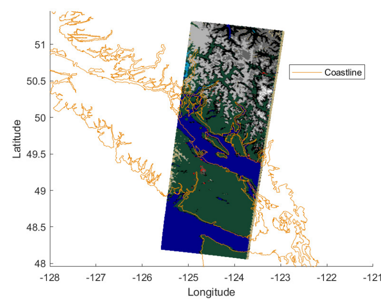
relative rigid body transformation. The identified coastline points in the image, p, are represented in red in fig. 4(a), and they present a significant error with respect to the actual coastline location, caused by the direct georeferencing method. The cloud points of the image are compared with the points present in a larger search area. Before applying the algorithm, the cloud points representing the coastline are heavily sub-sampled. The Iterative Closest point method is then applied, and the red points p are translated and rotated, obtaining the coastline-matched point q; the distance between the transformed points q and the database points must be minimized to georeference the image. The results of the simulation are depicted in fig. 4(b), where the matched points are represented in red.
In order to identify whether the algorithm converges to a solution, the distance between each matched point and the nearest actual coastal point is computed. A threshold on its median and mean can be imposed for operational reasons. If the imposed conditions are not met, the algorithm has not converged and no match between the points can be found. The indirectly georeferenced and classified picture is reported in fig. 4(c), where it is evident how the georeferencing is far more precise after the application of the algorithm with respect to fig. 4(a). The algorithm can be implemented onboard due to its relative simplicity with respect to other georeferencing methods. Even though this algorithm provides promising results, onboard tests will have to be carried out for an in-depth characterization of the method and its possible operational use. The main challenges with the indirect georeference approach are the automated identification of coastlines and the establishment of constraints to autonomously stop the algorithm after it has converged. Moreover, the image presents deformations due to the characteristics of the HSI camera and the classification algorithm, and a accurate georeferencing over the whole picture is not achievable with the available resources. However, this could be counteracted by applying the algorithm to subsets of the image.



(a) Directly georeferenced image



(b) Indirectly georeferenced image through coastline matching



(c) Georeferenced and classified image

Fig. 4. Georeferencing methods applied for an image taken over the Sechelt area in Canada on 6th June 2023.

3.5. Using georeferenced and classified images

A measurement can be directly evaluated onboard through the use of four different evaluations in terms of the information that it provides, and it can be accurately georeferenced. This approach could already be potentially added to HYPSO-1 operations; in particular, it would be possible to delete onboard the full cube associated with the capture, as the data throughput, storage, and downlink capacity available for CubeSats are limited. This allows, for example, to perform more captures per day.
Following the launch of HYPSO-2 in 2024, new possibilities will arise. As the satellite will include a SDR, direct communication with other agents could potentially be achievable after testing. A classified image could then be used to detect possible anomalies, as in the case of Harmful algal blooms. As monitoring this phenomenon is central to the HYPSO mission objective, Røysland [8] identified potential algae blooms as one of the classes labeled in the image. In order to detect the algae bloom and picture it with other sensors, precise georeferencing needs to be carried out in order to correlate the pixels expressing the anomaly to its exact location. Performing both steps onboard will then potentially support performing decision-making onboard HYPSO-2. In particular, if the image is not cloudy, coastlines are present in the picture, no attitude-pointing errors are detected, and an anomaly of interest is identified through classification, it would be possible to task the ASV directly from HYPSO-2. The ASV will then be directed to the area of interest, which is accurately georeferenced through the Iterative Closest Point algorithm.
A parallel approach would consist of running onboard target

detection on the full HSI cube [14], and identifying the algae bloom. Performing the previously described operational evaluations and algorithms, the identified target can be precisely located through the indirect georeference method. The information would then be transmitted to the ASV through the SDR, displacing the remote agent to the identified target area. Remote sensing observations are typically affected by distortions, noise effect and other type of data degradation, and the identification of a coastline match is therefore affected by these phenomena. One possible solution could consist in identifying part of the image to be compared with the ground truth of coastline. Comparing the whole image is more challenging as the amount of cloud points is larger, and the distortion in the image can be more relevant. In addition, the Iterative Closest Point algorithm applied in this work consist in rigid rotation and translation of cloud points; applying the algorithm to a less complex problem, such as sections of the image, could allow to add the scaling of the cloud points.

4. CONCLUSION

The introduction of onboard classification and a SDR on HYPSO-2 has paved the way to the adoption of new possible cooperative applications between the agents in the NTNU observational pyramid. This approach potentially allows to respond in near-real time (less than 2 hours from observation to cuing the next agent(s)) to anomalies, as data latency is minimized. The remaining open question regards evaluating if such an autonomous approach would be beneficial with respect to the timescale of the observed phenomenon. The alternative would consist of relaying the classified image to ground, where the image could be georeferenced, and tasking the agent from the ground station to observe the phenomenon. The georeferencing algorithm could be improved by matching parts of the image instead of the whole capture, as distortions and degradation in the image can affect the quality of the observation. The investigation and design of cooperative operations between the agents will then be completed by testing the whole pipeline when HYPSO-2 will be launched.

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