REGION OF INTEREST CODING IN PHOTSAT MISSION

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Abstract

The Institute of Space Studies of Catalonia (IEEC) coordinates the PhotSat project [1], which involves the development and construction of a satellite to monitor the 10 million brightest stars in the sky for at least two years. The scientific objective of this project is to complement the Large Synoptic Survey Telescope (LSST) [2] and the GAIA mission [3] by examining the intensity of stars. In the PhotSat mission, a CubeSat is expected to be launched at the end of 2025, with the mission of scanning the entire sky using two cameras—one with an ultraviolet (UV) detector and another with a visible (VI) detector. The desired configurations of the camera field of view (FOV) and the sensor step size are 8° and 4°, respectively, which will generate a total of 16.75 GB of image data that will need to be transmitted from the satellite to the Montsec ground station [4]. Since the download capacity to the Montsec station is limited to 8 GB per day, some compression is required.

The compression presented in this paper consists of two stages. The first stage uses an automatic object detection technique based on photometry [5], which analyzes the pixel intensities of the acquired data to identify the pixels corresponding to the Regions of Interest (ROI). This process adjusts the image so that only the ROIs are preserved, eliminating irrelevant pixels. In the second stage, the modified data is losslessly compressed using a prediction-based compressor and a contextual binary arithmetic encoder [6]. To provide contextual information around the ROI, the ROI can be expanded using the parameter ROI Extended Coding Pixels (RECP), which adds a specified number of pixels around the detected objects. Additionally, both the predictor and ROI coding can be independently enabled or disabled, allowing for faster execution and, under certain circumstances, improved coding performance.

Experimental results show that when our proposal is used with ROI coding disabled, all acquired data can be losslessly compressed to 5.86 GB. However, when ROI coding is enabled, compression performance improves significantly; for example, if RECP is set to 0 or 64, the acquired data can be compressed to 0.16 GB and 4.13 GB, respectively—a very significant compression.

Key words: Region of Interest; Compression; GB; space mission.

1. INTRODUCTION

The first space mission entirely led by the Institute of Space Studies of Catalonia (IEEC), in collaboration with the Autonomous University of Barcelona (UAB), the University of Barcelona (UB), the Polytechnic University of Catalonia (UPC), and the Spanish National Research Council (CSIC), aims to develop and build a nanosatellite designed to monitor the 10 million brightest stars in the sky. This mission, named PhotSat, generates a significant volume of 16.75 GB of image data daily due to the two sensors (UV and VI) that the CubeSat carries to capture the sky. The images, with 2 bytes per pixel and a resolution of 2048 × 2048 pixels, are produced at a rate of 1072 images per day, resulting from 16 daily orbits and 67 images per orbit. This large data volume must be downloaded by the Teleport antenna in Sant Esteve de la Sarga, located at the Montsec Observatory [4], with a limited downlink capacity of 8 GB per day. For this reason, the use of efficient

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compression techniques is essential to achieve the necessary reduction in data volume transmitted, thus ensuring the success of the mission.

In the regular operation of the mission, 50 frames per minute are recorded (one frame per second), followed by 10 seconds for satellite rotation adjustment and data processing. This set of 50 frames is accumulated to form a resulting image, which is averaged to obtain a mean value from the 50 frames. The averaged image obtained is the one that is compressed and subsequently transmitted. This process allows for a considerable reduction in data volume. However, in cases where transient phenomena—such as flares or supernova—are to be captured, individual frames may also be transmitted, further limiting the available transmission space.

The optical mission design is intended to provide a field of view (FOV) of 8° with a step size of 4°. However, the minimum requirements allow operation with a reduced FOV of 6° and a step size of 3°. In this minimum configuration, the number of images per orbit would increase to 89, generating a total data volume of 22.25 GB per day. This volume is unsustainable for the current transmission and compression capacities. The number of individual frames to be transmitted is also affected by this configuration, making it impossible to transmit the minimum requirement of 100 individual frames per day, as demanded by the science team.

To address this challenge, this paper presents an innovative image compression technique based on Regions of Interest (ROI), which aligns with low computational cost principles to optimize data management in space missions. This technique leverages photometry to identify and focus on the areas of the image containing stars and other astronomical objects, compressing only these ROIs while discarding the rest of the image. This allows for a significant reduction in the volume of transmitted data without compromising the essential information for the mission or the quality of the processed data.

The rest of the paper is organized as follows, Section 2 reviews different ROI coding techniques for satellite data coompression. Section 3 describes the proposed ROI coding technique, followed by Section 4 in where results are presented. Finally Section 5 concludes this article.

2. STATE OF THE ART

In the field of satellite image compression and detection, several innovative approaches aim to improve efficiency and accuracy in data analysis. A notable example in image compression is the work of Schwartz et al. [7]. This work proposes a methodology for satellite image compression focused on ROIs. The technique described uses image processing algorithms to automatically identify ROIs within an image, applying lossy compression to less significant areas while maintaining lossless or low-loss compression in the areas of greatest interest. This methodology optimizes bandwidth usage and ensures data quality in important regions.

On the other hand, Lu et al. [8] address object detection through collaboration between satellite and ground-based data. This work proposes a task-inspired framework that integrates satellite images with complementary data obtained through terrestrial means. This collaboration improves object detection accuracy and system robustness under various conditions. The integration of ground data helps overcome the limitations of satellite images, such as variations in resolution and atmospheric conditions.

Another relevant work is by Giordano et al. [9], which focuses on onboard hyperspectral image compression using ROI techniques. This work is notable for the use of GPUs to accelerate computations, enabling very efficient onboard compression. The proposed algorithm identifies ROIs in hyperspectral images and applies different levels of compression, maintaining high quality in areas of interest while reducing data size in less relevant areas. This approach not only optimizes bandwidth usage for transmissions but also minimizes real-time computational load onboard satellites.

The connection between these approaches is evident in how each addresses the need to improve quality and efficiency in satellite data management. While ROI compression optimizes data transmission to reduce the required bandwidth, collaboration with ground data can enrich the available information and improve object detection. Additionally, the use of ROI compression in onboard hyperspectral images, especially with the support of GPUs, allows for managing massive data volumes with efficient processing resource usage. Thus, combining these strategies could provide more robust solutions for monitoring and analyzing data in various applications, such as natural resource management, security, and environmental surveillance.

Despite significant advances in ROI compression for Earth observation, it is important to note that these techniques have primarily been applied to terrestrial remote sensing missions so far. There remains a wide

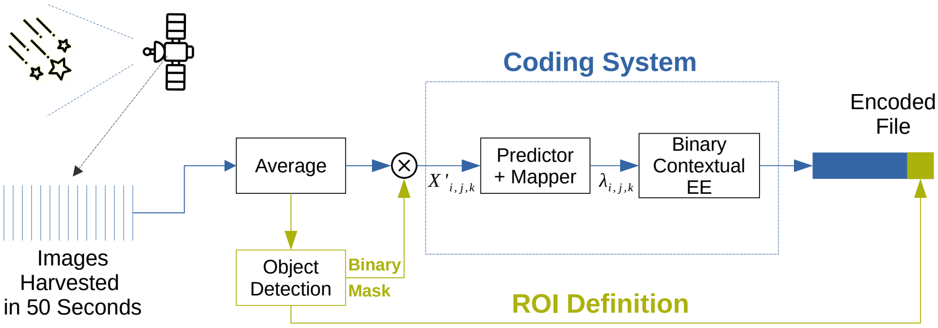


Figure 1: The complete compression pipeline from object detection to final compression. The standard compression system is highlighted in blue, while the ROI-specific processing steps are marked in dark yellow.

margin for exploration in the field of deep space observation. Space exploration missions could greatly benefit from the application of ROI compression techniques, especially to optimize the use of limited bandwidth and ensure better data quality in the study of astronomical phenomena. In this regard, the work we propose seeks to fill this gap, offering a novel contribution to ROI compression in the context of space observation.

3. PROPOSAL

The technique presented in this work addresses the detection of astronomical objects within an image and the resulting compression in an integrated manner. Initially, precise detection of the objects is carried out using a photometry software called SExtractor [5]. This algorithm analyzes the captured image, identifying which pixels correspond to objects and generating a file with the exact coordinates of these pixels. This set of coordinates is used to create a new image where pixels that do not contain objects are replaced with zeros. This process drastically reduces the amount of data to be processed, as only the pixels corresponding to objects are preserved, as described in Gonzalez-Conejero et al. [10].

To improve the quality of the decompressed data, spatial context can be added around the detected astronomical objects using the ROI Extended Coding Pixels (RECP) parameter. This parameter allows the inclusion of pixels surrounding the objects up to a certain radius. For example, if the RECP value is 4, the region around each object will be extended by 4 pixels in all directions. This approach provides more information about the immediate environment of each object during decompression, giving scientists a broader context for analyzing the objects. The RECP value can be adjusted according to the specific needs of the mission and scientific goals, though it will impact compression performance.

Once the image has been adapted to contain only essential pixel values, a lossless compression technique is applied to generate a bitstream. This compression technique is based on the compressor presented by Bartrina et al. [6], which uses the predictor from CCSDS 123.0-B-2 [11], followed by a mapper and an arithmetic entropy encoder. In this work, a simplified version of the original predictor is used to reduce computational costs. Unlike the original predictor, which dynamically adapts using weights, the modified predictor uses fixed weights, obtained through empirical studies, and performs a simpler function, suitable for applications with computational resource constraints. This predictor can be enabled or disabled depending on the mission needs; in some cases, disabling it may result in faster and more efficient compression, depending on the image complexity and object distribution. The entropy coding maintains the same context used in the previous article, ensuring optimal compression.

Figure 1 shows the complete pipeline proposed in this work, which consists of the arithmetic averaging of images captured in one minute, followed by data compression. In blue (labeled in Coding System), the standard compression process is shown, consisting of a predictor, a mapper, and a contextual binary entropy encoder (EE), generating a bitstream. Let I, J, and K be the number of columns, rows, and components of an averaged image X, and let $X_{i,j,k}$ be a pixel at location (i, j, k) in the image. X passes through the predictor, which estimates the current sample value $X_{i,j,k}$ using previously scanned samples. This predicted sample is denoted as $\hat{X}_{i,j,k}$. The predictor error is calculated as $\Lambda_{i,j,k} = X_{i,j,k} - \hat{X}_{i,j,k}$. Then, this prediction error $\Lambda_{i,j,k}$ is mapped to a non-negative integer $\lambda_{i,j,k}$. All these symbols $\lambda_{i,j,k}$ are encoded using a contextual binary EE.

When using our ROI coding technique, this pipeline is complemented by additional elements (shown in dark yellow for enhancement) that enable the selection of ROIs to reduce compression while maintaining scientific requirements. The image X is processed with the SExtractor algorithm, which detects objects and generates the corresponding coordinates. From these coordinates, a binary mask is created, where pixels (i, j, k) with a value of 1 indicate the presence of an astronomical object, and the rest indicate the absence of objects. This binary mask is combined with the averaged image, transforming it into an image X' , which will be compressed and transmitted. The predictor processes the image X', which is then compressed using our previously defined compressor. As a result, the bitstream is supplemented with the coordinate file of the objects identified as ROIs. This "side information" is compressed using the Lempel–Ziv–Markov chain algorithm and concatenated at the end of the bitstream, giving priority to the reconstruction of the images. This compression process optimizes the data volume while preserving the critical information necessary for scientific analysis, ensuring efficient and accurate transmission in resource-limited environments.

4. RESULTS

For obtaining results, various datasets were used. The first dataset is generated specifically for the mission in question. Since this mission has not yet been launched and no onboard images are available, a simulator was developed to generate images that approximately replicate real conditions. This simulator is based on data from the GAIA catalog [3], among other sources, and incorporates factors such as expected noise, cosmic ray impacts, and other potential objects that could appear in the images captured in space. The aim is to produce simulated images with a high degree of fidelity for initial testing. The scientists of the mission produced two datasets: one with a sparse number of objects and another with a higher density of objects, making it more challenging to compress. This paper focuses on the latter, more complex dataset.

In addition to the simulated images, tests were conducted using various real astronomical datasets provided by renowned telescopes and observatories. These include datasets from the Isaac Newton Telescope (INT) and the Jacobus Kapteyn Telescope (JKT). These datasets are available in the article [12] and correspond to images captured by telescopes located at the Roque de los Muchachos Observatory in La Palma, Canary Islands.

The use of these real datasets is essential for validating the proposed compressor, as the simulated images, while designed to accurately replicate the conditions the mission will face, are not real images. Testing the technique with real data allows for evaluating its effectiveness in a broader and more diverse environment.

The Consultative Committee for Space Data Systems (CCSDS) developed the second edition of the CCSDS-123.0-B-1 standard [13], known as CCSDS 123.0-B-2, titled "Low-Complexity Lossless and Near-Lossless Multi-spectral and Hyperspectral Image Compression" [11]. The results of the proposed technique were compared with those obtained using the CCSDS 123.0-B-2 standard. This comparison is crucial for determining the efficiency of the new method in relation to established standards for space missions.

This section presents performance results of the ROI coding technique, recovering the ROIs without loss. Compression performance results are provided for the two configurations (FOV 8° / Step 4° and FOV 6° / Step 3°). Additionally, visual results of the proposed technique are shown.

In Table 1, the results obtained in bits per sample (bps) are shown for both compression with and without ROI coding. The results indicate that our compressor, even without using ROI coding, offers better performance than the CCSDS 123.0-B-2 standard. This is valid for both the simulated images from the mission dataset and the real images from the INT and JKT datasets, where our compressor also outperforms the CCSDS 123.0-B-2 standard.

For standard compression, enabling the predictor is usually advantageous. However, when applying ROI coding with low RECP values, the results are better if the predictor is not activated. Up to a RECP value of 16, the system performs better without prediction, as the limited context around the ROIs does not provide enough information for accurate predictions. This leads to an increase in prediction errors, making compression without prediction more efficient. From RECP = 16 onwards, when the context radius around the objects increases, the predictor starts to perform better due to access to more contextual information, which allows for more accurate predictions and, therefore, improves compression performance. As the RECP value continues to increase, the difference between enabling or disabling the predictor becomes more significant, achieving a substantial improvement in data size when prediction is enabled.

Table 1: Comparison (in bits per sample) between standard compression using our codec with and without the Predictor (P) and CCSDS 123.0-B-2, and ROI compression for the mission dataset, INT, and JKT datasets.

		Dataset 2		INT		JKT	
No ROI Coding	CCSDS 123.0-B-2	6.48		5.54		5.82	
	Regular compression	P = false	P = true	P = false	P = true	P = false	P = true
		6.50	**5.59**	6.42	**5.30**	6.93	**5.57**
ROI Coding	RECP = 0	**0.16**	0.36	**0.11**	0.16	**0.20**	0.22
	RECP = 1	**0.27**	0.55	**0.14**	0.20	**0.23**	0.24
	RECP = 2	**0.40**	0.71	**0.17**	0.23	**0.24**	0.26
	RECP = 4	**0.70**	1.08	**0.23**	0.30	**0.28**	0.30
	RECP = 8	**1.42**	1.74	**0.38**	0.46	**0.38**	0.40
	RECP = 10	**1.77**	2.02	**0.47**	0.54	**0.43**	0.46
	RECP = 12	**2.09**	2.25	**0.56**	0.62	**0.49**	0.51
	RECP = 14	**2.38**	2.45	**0.65**	0.71	**0.56**	0.58
	RECP = 16	**2.62**	**2.62**	**0.75**	0.79	**0.63**	0.64
	RECP = 32	3.73	**3.38**	1.50	**1.41**	1.31	**1.24**
	RECP = 64	4.48	**3.95**	2.85	**2.53**	2.82	**2.47**
	RECP = 128	5.22	**4.56**	4.67	**3.97**	5.08	**4.20**

Table 2: Comparison (in GB per day) between Not compressed, CCSDS 123.0-B-2, regular compression using our codec and ROI compression for the mission dataset. For our proposal results enabling and disabling the prediction (P) procedure are reported.

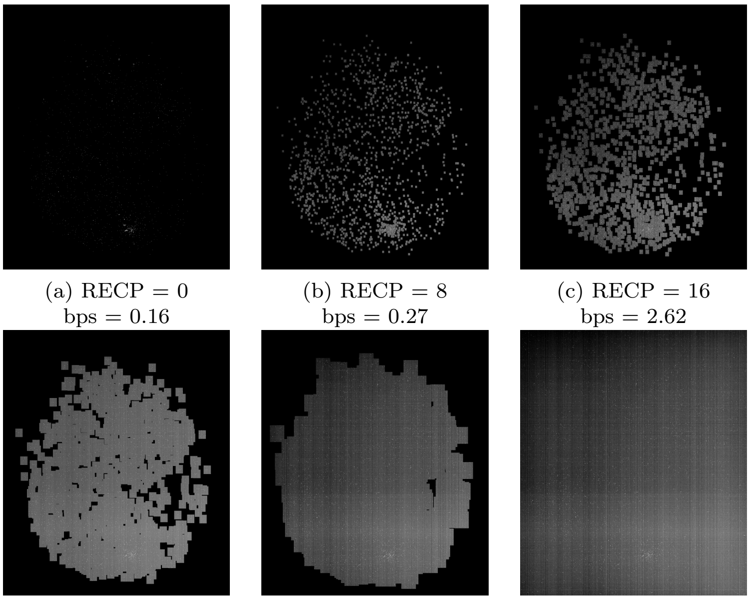
		Configuration 8°/4°		Configuration 6°/3°	
No ROI Coding	Not compressed	16.75		22.25	
	CCSDS 123.0-B-2	6.78		9.01	
	Regular compression	P = false	P = true	P = false	P = true
		6.80	**5.86**	9.03	**7.78**
ROI compression	RECP = 0	**0.16**	0.37	**0.22**	0.49
	RECP = 1	**0.29**	0.58	**0.38**	0.77
	RECP = 2	**0.41**	0.74	**0.55**	0.98
	RECP = 4	**0.74**	1.14	**0.98**	1.51
	RECP = 8	**1.49**	1.82	**1.98**	2.42
	RECP = 10	**1.86**	2.11	**2.47**	2.80
	RECP = 12	**2.19**	2.36	**2.91**	3.13
	RECP = 14	**2.49**	2.57	**3.30**	3.41
	RECP = 16	**2.74**	**2.74**	**3.64**	**3.64**
	RECP = 32	3.91	**3.54**	5.91	**4.70**
	RECP = 64	4.69	**4.13**	6.23	**5.49**
	RECP = 128	5.47	**4.78**	7.26	**6.34**

It is important to note that the bps values shown in Table 1 in the ROI compression section represent the total bps, i.e., the sum of the bitstream generated from compressing the image and the "side information". In the case of the mission dataset (Dataset 2), the "side information" occupies an average of 0.035 bps. For the INT and JKT datasets, the bps consumption for the "side information" is notably lower, with average values of 0.004 and 0.003 bps, respectively. This reflects that, even when including the "side information," the additional cost in terms of compression is minimal, especially for the INT and JKT datasets.

For all the datasets analyzed, applying compression with ROIs allows for a significant reduction in data volume. Specifically, with compression at RECP = 0, a compression performance of 97.14% is achieved for the Dataset 2, 97.91% for the INT dataset, and 96.41% for the JKT dataset. These figures highlight the effectiveness of the ROI compression technique compared to compression without ROIs.

The results presented in Table 2 refer to the gigabytes (GB) occupied by the mission dataset depending on the configuration used. For these calculations, the same compressors and techniques as in Table 1 were applied. Analyzing the size of the compressed images is crucial for determining the number of GB that will need to be sent to Earth and the number of individual frames that can be transmitted, depending on the available GB before reaching the 8 GB daily limit. The individual frames are images with a resolution of 2048 × 2048 pixels and 2 bytes per pixel, which means they occupy a total of 8 MB per image.

Finally, Figure 2 shows a visual comparison of the proposed ROI coding technique of a simulated image for



(a) RECP = 0
bps = 0.16

(b) RECP = 8
bps = 0.27

(c) RECP = 16
bps = 2.62

(d) RECP = 32
bps = 3.38

(e) RECP = 64
bps = 3.95

(f) Regular Compression
bps = 5.59

Figure 2: A set of images from the Photosat mission dataset with the RECP parameter set to (a) 0, (b) 8, (c) 16, (d) 32, (e) 64, and (f) the Regular Compression. Note: Electronic visualization is recommended for optimal viewing.

RECP values of 0, 8, 16, 32, 64, and the regular compression, for each image the bps needed for coding losslessy are also reported.

4.1. Sensor Configuration with FOV = 8°, Step = 4°

With this configuration, the images in RAW format occupy a total of 16.75 GB. By applying regular compression (without ROI coding), the minimum required of 8 GB per day can be achieved, generating approximately 5.86 GB using prediction. This compression would allow for the transmission of up to 274 individual frames, as there would be an additional 2.14 GB available for transmission. In the case of applying compression with the CCSDS 123.0-B-2 standard, it would be possible to send up to 155 individual frames. However, if ROI compression is applied, the total volume can be reduced to just 0.16 GB when the predictor is not used. This significant reduction highlights the efficiency of ROI compression in managing data space and optimizing image transmission. Furthermore, the number of frames would increase to 1003 frames.

4.2. Sensor Configuration with FOV = 6°, Step = 3°

This configuration is more demanding, and the results obtained are much tighter in terms of compression. In RAW format, the images occupy 22.25 GB. Whether applying standard compression without ROI or predictor, or using the CCSDS 123.0-B-2 code, the minimum required of 8 GB per day is not achieved. To meet this goal, it is necessary to activate the predictor, but even then, the window for sending individual frames is considerably reduced. With 7.78 GB per day, only 28 individual frames could be transmitted, while scientists have established that a minimum of 100 frames per day is needed. In this context, ROI compression becomes crucial. By using the proposed technique and applying ROIs, it is possible to reduce the 7.78 GB down to just 0.22 GB per day, allowing for the transmission of up to 995 daily frames. If scientists require more context when applying ROIs, using an RECP of 128 could achieve a compression that results in 6.34 GB, permitting the sending of 212 frames per day.

5. CONCLUSION

This work presents an image compression technique based on ROIs applied to astronomical images in space missions. Experimental results demonstrate a significant improvement in compression efficiency when employing the ROI technique, notably reducing the volume of transmitted data compared to conventional compression methods. Compared to the CCSDS 123.0-B-2 standard, the use of ROI not only achieves higher compression rates but also preserves the quality of scientific information in the areas of interest. Specifically, with a configuration of a FOV of 8° and a step of 4°, data is reduced from 16.75 GB in RAW format to 5.86 GB with standard compression, and further down to 0.16 GB with the proposed ROI technique (RECP = 0). In scenarios with more restrictive configurations, such as a FOV of 6° and a step of 3°, where compression is even more critical, the use of ROI reduces the data volume from 22.25 GB in RAW and 7.78 GB with standard compression to just 0.22 GB with ROI (RECP = 0).

From the results, two main conclusions can be drawn. First, the proposed compressor consistently delivers better results in terms of compression, even when using only standard compression, compared to CCSDS 123.0-B-2. Second, the proposed technique of ROI coding leads to a significant improvement in compression, further reducing the size of the files to be transmitted. This result underscores the importance of selecting areas of interest in astronomical images, as it allows for more precise and efficient compression compared to standard compression. These results demonstrate that ROI-based compression is an efficient and viable solution for space missions like PhotSat, where limitations in transmission capacity are a critical factor.

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