THE SURPRISE DEMONSTRATOR: A SUPER-RESOLVED COMPRESSIVE INSTRUMENT IN THE VISIBLE AND MEDIUM INFRARED FOR EARTH OBSERVATION

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ABSTRACT

Earth Observation (EO) applications and products can greatly benefit from increased spatial resolution and revisit time of EO optical payloads. On the other hand, increasing spatial resolution poses several technological challenges, both in terms of detector arrays and data bandwidth. In this paper, we introduce the concept of a super-resolved compressive instrument – the SURPRISE demonstrator – which is being developed to address a super-spectral payload for Earth Observation working in the visible and in the medium infrared with enhanced performance in terms of at-ground spatial resolution, innovative on-board data processing and encryption functionalities. To achieve this goal, the SURPRISE demonstrator relies on two main technologies: Spatial Light Modulator technology and Compressive Sensing. Here we present the demonstrator's concept, its overall architecture and the approach used for image reconstruction.

1. INTRODUCTION

While Earth Observation (EO) data has become ever more vital to understanding the planet and addressing societal challenges, applications are still limited by revisit time and spatial resolution. Though low Earth orbit missions can achieve resolutions better than 100 m, their revisit time typically stands at few to several days, limiting capacity to monitor dynamic events. Geostationary (GEO) missions instead typically provide data on an hour-basis but with spatial resolution limited to 1 km, which is insufficient to understand local phenomena.

In this respect, the Compressive Sensing (CS) paradigm can pave the way to a new concept of optical sensors for space applications, with advantages in terms of data throughput and low cost technology. Several CS-based instrumental concepts were already proposed in the literature, mainly for spectroscopic applications with the aim of reducing the data throughput of the sensors, yielding in some cases to the implementation of demonstrators or prototypes (e.g. [1]-[3]). Only few of them, however, specifically addressed space applications ([4]-[7]).

In this paper, we present the SURPRISE project - recently funded in the frame of the H2020 programme – that gathers the expertise from eight partners across Europe. Its main goal is to implement a demonstrator of a super-spectral EO payload - working in the visible (VIS) - Near Infrared (NIR) and in the Medium Wavelength InfraRed (MWIR) and conceived to operate from GEO platform - with enhanced performance in terms of at-ground spatial resolution, and featuring innovative on-board data processing and encryption functionalities.

The SURPRISE demonstrator aims at improving the spatial resolution of EO payloads by addressing a compressive sensing-based architecture based on the use of a Spatial Light Modulator (SLM) as a core element. The latter will be used to devise a super-resolution configuration that will be exploited to increase the at-ground spatial resolution of the payload, without increasing the number of detector's sensing elements at the image plane. The Compressive Sensing (CS) approach will offer further advantages for handling large amounts of data, as is the case of superspectral payloads

with wide spectral and spatial coverage. It will enable fast on-board processing of acquired data for information extraction, as well as native data encryption on top of native compression. By introducing for the first time the concept of a payload with medium spatial resolution (few hundreds of meters) and near continuous revisit (hourly), SURPRISE can lead to an EO major breakthrough and complement existing operational services.
In the following sections, we recall the concepts underpinning the SURPRISE project, we present the demonstrator's architecture and its working principle/Finally, we describe the image reconstruction methodology and the advantages offered in terms of on-board data processing and encryption functionalities.

2. THE SURPRISE BASIC CONCEPTS

The SURPRISE demonstrator relies on two pillars: CS and SLM technology.
CS is used to optimise data acquisition (e.g. reduced storage and transmission bandwidth requirements) and to enable encryption functionalities and novel onboard processing, with the aim to improve timeliness, shortening time needed to extract information from images and possibly generate alarms.
SLM is used to implement the CS paradigm and achieve a super-resolution architecture. A proof-of-concept will be provided from the implementation of a demonstrator.
Thus, the major objective of the SURPRISE's demonstrator is to show how the use of SLM technology and CS approach can be exploited to yield a significant improvement of the performance of EO super-spectral payloads in the visible (VIS), near- (NIR) and medium-wave infrared (MWIR), in terms of their spatial resolution, onboard data processing and data encryption capabilities.

2.1. Compressive Sensing

CS is an innovative signal acquisition technique that benefits from the feature of many natural signals being highly correlated. A high correlation entails the existence of a domain (integral transform) in which the signal is sparse, and only a small fraction of the transform coefficients is significantly different from zero. Nyquist–Shannon sampling theorem states that an arbitrary signal, where the highest frequency is less than half of the sampling rate, can be reconstructed perfectly. The main idea of CS is that, with prior knowledge about the signal's sparsity, the signal can be reconstructed using fewer samples. In a standard signal compression strategy, data is first sampled and then compressed to reduce final data volume. CS, on the other hand, aims to reduce the volume of acquired signal samples. CS techniques rely on the acquisition of a set of spatially integrated measurements of the scene of interest, modulated by a suitable spatial pattern. In practice, this is obtained by using an SLM that physically performs the scalar product between a random pattern and the incoming light, followed by an optical assembly that concentrates signal on a single element detector that acquires it. Signal reconstruction requires identification of the sparsest signal that matches the available measurements, which can be performed using, amongst others, linear programming techniques.
The idea behind the concept of the SURPRISE demonstrator is the single-pixel camera [1]. Figure 1 shows the basic working principle of a single-pixel camera: the image produced by the collection optics is modulated at the image plane by a SLM - acting as a coding mask - and the signal transmitted through the SLM is focused by an optical condenser on a single-pixel detector. Finally, a set of measurements – each corresponding to a different modulation pattern applied to the image – is used to reconstruct the original image by using suitable CS reconstruction algorithms.

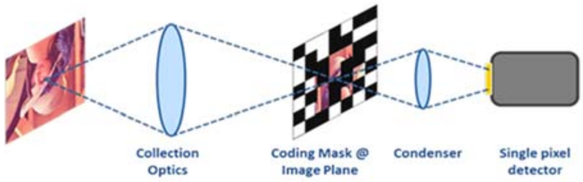

Figure 1. SLM technology and single pixel camera.

A CS-based instrument's architecture can be exploited to acquire fewer measurements than the corresponding image pixel numbers. According to CS theory, an N-pixel detector can be replaced with a single-pixel camera performing a number of measurements equal to p*N, with p usually ranging from 0.01 to 0.5. Quality of the reconstructed image is correlated with parameter p. Hence, a CS-based system acquires inherently compressed data, so acquisition and compression steps are merged in a single process and onboard data compression is no longer needed to reduce data amounts to be stored and/or transmitted.

2.2. SLM Technology and Super-Resolution

Although CS has mainly been used for merging data acquisition and compression into a single step, it can also be used to acquire images whose resolution after reconstruction is increased up to that of the coding pattern applied. This concept is referred to as the super-resolution approach.
A super-resolution imaging system is an imaging system whose resolution is enhanced with respect to its nominal one. Many techniques can obtain super-resolution, for example combining multiple low-resolution images with sub-pixel shifts. Computational Imaging with coded apertures relies on a different approach for high-resolution imaging. By using low-resolution measurements, the optical modulation of the light field occurs before it is digitally acquired. In this way, high spatial frequencies can be recovered from several

encoded measurements employing suitable algorithms. Many Computational Imaging systems employ an SLM to code the incoming light, and CS can be seen as a limit case of Computational Imaging, where the number of measurements is lower than the number of pixel of the high-resolution image to be reconstructed.

3. THE SURPRISE DEMONSTRATOR

The SURPRISE demonstrator is based on a CS-based architecture relying on the use of an SLM as core modulating device, with the aim of demonstrating the working principle and relevant benefits offered by these technologies for the development of an EO payload in the VIS-NIR and MWIR spectral regions. The demonstrator's requirements and specification (e.g. number of spectral channels, radiometric accuracy, fore-optics, etc.) are necessarily simplified with respect to those of a corresponding operational EO payload. Despite this, the design will be scalable to more challenging – and expensive – specifications for the future implementation of an EO payload.
The demonstrator is conceived as a whiskbroom spectral imager working in the VIS-NIR (> 10 channels) and MWIR (two channels: channel#1 with central wavelength at 3.3 µm with 0.4-µm FWHM; channel#2 with central wavelength at 4.0µm with 0.4-µm FWHM), able to acquire super-resolved images of a generic target by using an implementation of a CS architecture.
The instrument's working principle is based on the use of an SLM to increase the spatial resolution of the image observed by the instrument's fore-optics. The acquisition of several measurements - each corresponding to the integrated value of the image modulated by means of several SLM patterns - is used to reconstruct the superspectral image with a higher spatial resolution. By using suitable modulation masks on the SLM, and by applying CS techniques, the image can be reconstructed by acquiring a total number of measurements smaller than the number of pixels of the reconstructed image.

Figure 2 illustrates the working principle of the SURPRISE demonstrator.
A generic target is imaged by a collection optics. The image (hereinafter referred to as 'macropixel') is focused on an SLM providing spatial coding of the target at higher spatial resolution. Such spatially coded image is then spatially integrated (averaged) by a condenser lens and acquired by a single pixel sensor.

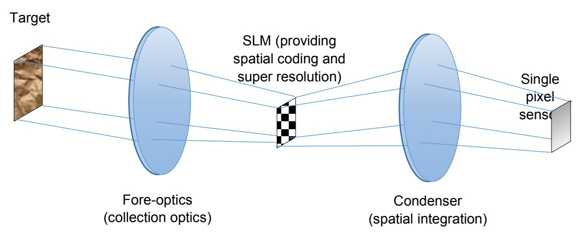

Figure 2. SLM technology and super-resolution.

The acquisition is iterated by using a sequence of spatial coding masks. If the spatial resolution granted by the SLM is N x N pixels (each of which hereinafter referred to as 'micropixel'), a linearly independent sequence of N x N spatially coded acquisitions allows the reconstruction of the macropixel super-resolved into N x N micropixels. By applying CS theory, the number of acquisitions for an exact reconstruction of the super-resolved macropixel (N x N acquisitions) can be reduced, obtaining a (lossy) N x N super-resolved reconstructed image. The loss of information depends on the sparsity of the scene in the compressed domain (defined by the spatial coding sequence).
Figure 3 shows a block diagram of the demonstrator's architecture in which mechanical, electronic and optical parts are highlighted.

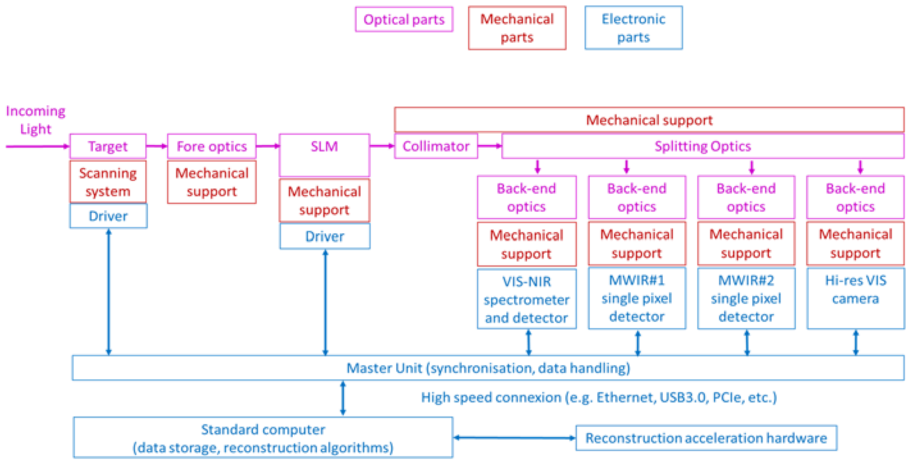

Figure 3. The SURPRISE demonstrator's overall architecture.

The scene is scanned along two axes by means of a suitable scanning system. The fore-optics provides the image of the observed portion (target) of the scene on the image plane field stop at which the SLM is placed. The image captured in the instrument's Instantaneous Field Of View (IFOV) corresponds to a 'macropixel' on the SLM (Figure 2). Spectral splitting is applied after the SLM-based coding stage by means of dichroic mirrors and is followed by the spatial integration stage implemented by the condensers. The signal is further spectrally filtered (or dispersed by the spectrometer for the VIS-NIR channels) and finally acquired in spectral bands of interest by suitable detectors.
The overall architecture of the SURPRISE demonstrator must also include a suitable master unit that guarantees proper synchronisation and data handling. At the beginning of the sequence of CS measurements, the target scanning system must be positioned so as a given portion of the scene (target) is seen by the instrument's IFOV; secondly, a modulation mask must be set on the SLM; thirdly, acquisition by each detector can be triggered. Once the integration time has run for all the detectors, another mask must be set on the SLM and a new acquisition by the detectors can be triggered. These operations are repeated until the given number of CS measurements is reached. At the end of the sequence, the scanning system makes another portion of the scene being observed by the instrument's IFOV and the sequence of operations can be run again until all the scene is scanned.
The measurement rate is critical for SURPRISE-like instruments. It must be as high as possible but is limited by the time taken by parts with mechanical drive (e.g. the scanning system or the SLM) to move from one position to another and by the integration time requested by the detectors to achieve a given SNR. The timely sequence of operations for a measurement is under the control of a master unit. This unit managed the time at which an operation is achieved by one of the subsystems. In addition, it collects the data generated by the detectors and provides data to the SLM defining the position of the micromirrors or the modulation mask. The respective interface of the subsystems with the master unit is of central importance to successfully implement the whole system.

4. IMAGE RECONSTRUCTION

CS theory has demonstrated that a signal can be sensed in a linear fashion as $= A\boldsymbol{x}$ (Figure 4), and reconstructed with high probability when it exhibits sparsity in some transformation domain.
Several image recovery algorithms from compressive measurements have been proposed, also for astronomical data compression and astronomical remote sensing [1] and the literature on this topic is extremely vast.

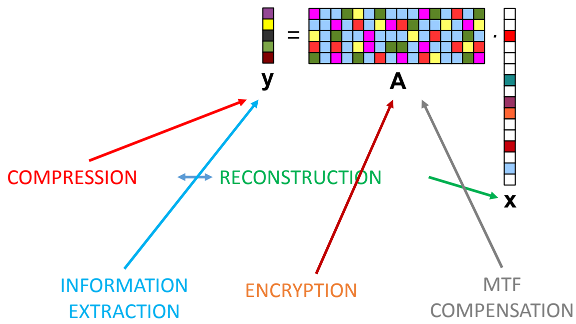

Figure 4. CS and the sensing process.

Most existing reconstruction techniques exploit image sparsity in a given domain (wavelet, discrete cosine transform, gradient domain and so on) and attempt to perform the reconstruction with different approaches: greedy algorithms, iterative thresholding algorithms, convex relaxation algorithms or non-convex relaxation algorithms. However, also for moderate-sized images, the reconstruction can be still very slow due to the complexity of the problem. For this reason, a more convenient and popular solution for image reconstruction is minimizing the Total Variation pseudo-norm. This approach can be particularly useful for natural images but for multidimensional signals, e.g. multispectral images with which are dealt with in the SURPRISE project, a serious problem arises regarding the computational complexity of the reconstruction process.
Fortunately, in the recent years, deep learning algorithms have demonstrated the generalization capacity of the neural networks improving considerably the performance of previous state-of-the-art technologies in many fields, including image processing and image reconstruction. Deep learning techniques are able to achieve good results in terms of time and quality reconstruction and for these reasons we will rely on them in the SURPRISE project. Deep learning can take advantage of a training set in order to learn a domain in which the image is as sparse as possible, leading to very effective reconstruction algorithms. Results reported in the literature (e.g. [16]) show a significant improvement in the reconstruction of the sensed image. Moreover, deep learning methods typically have lower complexity that conventional reconstruction methods, which solve complex inverse problems.

5. DATA ENCRYPTION

CS can provide native encryption, avoiding the need of a payload-specific encryption module, and relieving the duties to be performed by the encryption module on the telecommand&control system. As introduced in [9], CS can be seen as a symmetric-key cryptosystem employing the sensing matrix as an encryption key. However, compressive encryption provides perfect indistinguishability only for equal energy signals and

when the sensing matrix is made of real-valued Gaussian i.i.d. entries and is re-generated at each encryption [10].
As far as encryption is concerned, in SURPRISE we aim at embedding an encryption functionality in the optical payload, to be performed directly during the image sensing process. We will translate the theoretical results available so far into the first native encryption scheme for a space imaging instrument. However, the design has to take into account a number of constraints. In order to have a practical design for space applications, one has to combine the optical design requirements, the data security requirements, as well as the ability to extract information from the data during on-board processing. Notably, the acquisition architecture involving the SLM will impose a sensing matrix with a specific structure. As highlighted in the literature, structured sensing matrices provide a trade-off between the confidentiality of the data and the ability to extract the desired information from it [11], so in SURPRISE will be carefully analyse this trade-off taking into account the instrument design constraints.
Moreover, the SLM is only able to implement sensing matrices with binary entries. Even though preliminary results show that quantization of sensing matrix entries has a limited impact on the confidentiality of compressive encryption [13], this aspect should be carefully evaluated in the SURPRISE design. Finally, the need to continuously update the sensing matrix will impose the design of suitable encryption modes to support confidentiality for the corresponding instrument operating modes. In this respect, SURPRISE will investigate a counter mode of operation that can be implemented relying on an efficient stream cipher module [12]. This design can also enable the transmission of the signal energy on a separately encrypted channel for scenarios in which the maximum confidentiality level is required.

6. ONBOARD INFORMATION EXTRACTION

The CS framework enables image acquisition in an already compressed format thanks to direct optical construction of measurements as random projections of the scene. This low-complexity encoding is traded for a more computationally demanding decoding phase which performs image reconstruction from the low-dimensional measurements. As long as reconstruction can be performed at the ground segment, the computational demands can be easily met. However, one might want to perform inference tasks on the images directly onboard of the acquisition platform.
Fortunately, a number of important inference problems can be efficiently solved in the compressed domain [14], without the need to perform expensive image reconstruction.
CS measurements are acquired as random projections of a signal, which can be written as:

$$\boldsymbol{y} = \mathrm{A}\boldsymbol{x}.$$

The key property that allows information processing directly on measurements $\boldsymbol{y}$ is that the sensing matrix implements a stable embedding, i.e. a mapping between vector spaces that approximately preserves distances between points. A good sensing matrix provides a stable embedding by satisfying the Restricted Isometry Property (RIP):

$$(1-\varepsilon)\|\boldsymbol{u}-\boldsymbol{v}\| \leq \|\mathrm{A}(\boldsymbol{u}-\boldsymbol{v})\| \leq (1+\varepsilon)\|\boldsymbol{u}-\boldsymbol{v}\|$$

for signals $\boldsymbol{u}$,$\boldsymbol{v}$ that are k-sparse in some orthonormal basis.
In a *classification* problem, one is concerned with discriminating signals belonging to different classes by drawing a separator in the space the signals live in.
One can see that approximately preserving distances allows to effectively discriminate signals belonging to different classes even if they mapped to the reduced-dimensionality space of CS measurements.
Let us consider a binary classification problem where we want to detect the presence or absence of a signal of interest This is a classic hypothesis testing problem where the null hypothesis corresponds to only observing noise, while the alternative hypothesis is observing a signal $\boldsymbol{s}$ corrupted by noise. One can prove that given compressive measurements $\boldsymbol{y}$ and knowing the template signal $\mathbf{s}$, the following is a sufficient statistic for the detection problem:

$$t = \boldsymbol{y}^T(\mathrm{A}\mathrm{A}^{\mathrm{T}})^{-1}\mathrm{A}\mathbf{s} = \boldsymbol{y}^T\boldsymbol{z},$$

where $\boldsymbol{z}$ can be efficiently precomputed. Comparing the statistic t with a threshold solves the detection problem. Crucially, it is known that this compressive solution to the inference problem has a performance close to the one in the uncompressed domain, despite only having access to the signal measurements.
Another task that can be performed in the compressed domain is signal filtering, provided that a suitably structured sensing matrix is used. When a circulant sensing matrix is used, it is possible to compute the measurements of the filtered version of the signal by filtering the original measurements, thus avoiding signal reconstruction [15]. However, the requirement on using circulant sensing matrix could clash with the optical instrument design which induces a special structure on the sensing matrix. A tradeoff with security requirements is also present as it is known that circulant matrices leak the autocorrelation of the acquired signal[11] [11].
Finally, we can also generalize the approachto arbitrary inference problems and algorithms without the need for full reconstruction if we accept some degradation in performance. In fact, an inexpensive low-quality reconstruction could be obtained via a linear method:

$$\hat{\boldsymbol{x}} = \boldsymbol{R}\boldsymbol{y}.$$

The operator $\boldsymbol{R}$ can be either chosen as the right inverse of the sensing matrix:

$$\boldsymbol{R} = \mathrm{A}^T(\mathrm{A}\mathrm{A}^T)^{-1}$$

leading to the reconstruction with minimum Euclidean norm fitting the measurements.
Alternatively, one can learn a better operator from training data, by solving:

$$\boldsymbol{R} = argmin_{\boldsymbol{R}}\|\boldsymbol{RY} - \boldsymbol{X}\|_F^2 = \boldsymbol{XY}^T(\boldsymbol{YY}^T)$$

where $\boldsymbol{X}$ stacks all the training signals by columns and $\boldsymbol{Y} = \mathrm{A}\boldsymbol{X}$.
Accessing the full signal reconstruction, albeit at low quality, enables arbitrary algorithm to be deployed for onboard inference.

7. CONCLUSIONS

In summary, the EU-funded SURPRISE project aims at leveraging CS to design and prototype an innovative imaging system in the VNIR/MWIR wavelength, and develop the related technologies. Advances are expected in hardware (spatial light modulator, optical design, electronics) as well as software (CS reconstruction algorithms, image analysis, encryption). This will boost European competitiveness in several key cutting-edge technologies.

8. ACKNOWLEDGEMENTS

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