Hyperspectral image compression based on data fusion and spectral unmixing techniques.

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***Abstract*—The onboard compression of remote sensed hyperspectral images is an important task nowadays. One of the main difficulties is that the compression of these images must be performed in the satellite which carries the hyperspectral sensor. Hence, this process must be performed by space qualified hardware, having area, power and speed limitations. Moreover, it is important to achieve big compression ratios without compromising the quality of the decompress image. In this work two new strategies for compressing hyperspectral images in a efficient way are proposed. These strategies are based on the concepts of data fusion and spectral unmixing. According to the results obtained within this work, it is concluded that both methodologies provide important advantages with respect to the state-of-the-art methods.**

Hyperspectral imagen compression, ultraspectral image compresion, onboard compression, hyperspectral and multispectral data fusion, FUN algorithm, CoEf-MHI algorithm.

I. Introduction

There are satellites which carry hyperspectral sensors that are able to collect huge amount of data. The hyperspectral images collected by this kind of sensors have multiple applications in remote sensing, however, the amount of information that these sensors are able to collect is typically much bigger than the amount of information that the satellites are able to transfer to the earth. For this reason, the hyperspectral image compression have become an important task. However, the compression of hyperspectral images presents some difficulties. First of all, it is important to achieve high compression ratios in order to be able to send the collected images to the earth, but without losing much information in the compression and decompression process, or the images would not be useful. Moreover, the compression process must be executed onboard, using space qualified hardware, which results in area, power and speed restrictions. Hence, the algorithms which performs the compression process must be as hardware-friendly and parallelizable as possible. The compression process is also desirable to be fault tolerance.

Within this work, two new methodologies for compressing and decompressing hyperspectral images have been proposed, which have some important advantages with respect to the state-of-the-art methods for this task. The first methodology simply splits the hyperspectral image into two new much smaller images: a high resolution multispectral image and low resolution hyperspectral one. These two images can be directly transfer to the earth and then, these two images are fused, for reconstructing the initial one, using one of the existing algorithm for fusing hyperspectral and multispectral images. The second method proposed is based on the Fust algorithm for linearly UNmixing hyperspectral image (FUN) [1]. This method first extracts some orthogonal vectors using a modified version of the FUN algorithm, which are then used to project the hyperspectral image onto the space spammed by these vectors. The projected image, which is much smaller than the original one, and the projection vectors extracted, are directly transfer to the earth. The projected image can be directly decompress by multiplying it with the projection vectors.

In order to verify the goodness of our proposals, some simulations have been performed, using real hyperspectral images acquired by different sensors. These images have been also compressed and decompressed using some of the state-of-the-art algorithms for this task. According to the results obtained in the simulations performed, it can be concluded that both methodologies produce high compression ratios with few losses of information. Moreover, the proposed methodologies represent important advantages with respect to the state-of-the-art compression algorithms for hyperspectral images in term of complexity.

II. Methodology based on data fusion

There exist many algorithms which are able to accurately fuse a high resolution multispectral image and a low resolution hyperspectral one in order to obtain a high resolution hyperspectral image. Some of the most important algorithms for this task are the Generalized Gram-Schmidt Adaptive (GGSA) algorithm, the Generalized Local Minimum Square Error (GGLMMSE) algorithm, the Computationally Efficient algorithm for fusing Multispectral and Hyperspectral images (CoEf-MHI), the Couple Nonnegative Matrix Factorization (CNMF) algorithm, the Hyper Spectral image Superresolution (HySure) algorithm and the Bayesian Sparse and Bayesian Naive algorithms [2, 3, 4, 5, 6].

The proposed method for compressing and decompressing hyperspectral images make use of the fusion process in the sense that, it first divides the image to be compress in two much smaller images which can be transfer to the earth, and then these two images are fused using one of the aforementioned fusion algorithms.

A. *Compression phase.*

The hyperspectal image to be compressed is divided in two much smaller images. The first image must be a multispectral image with the same spatial resolution than the image to be compressed. This image can be obtained, band by band, in two different ways. The first way to obtain each band of this multispectral image is by simply selecting one of every r_b bands of the image to be compressed. The second way to obtain each band of the multispectral image is by performing the mean of every r_b bands of the image to be compressed. The second image that must be obtained from the image to be compressed is a spatial degraded version of it. This can be done by performing a bilinear interpolation or by simply selecting one of every r_p^2 pixels of the image to be compressed. Being r_p the ratio between the linear spatial resolution of the image to be compressed and the linear spatial resolution of its degraded version. The compression ratio achieved depends of the r_b and r_p selected values, as shown in the equation (1):

$$CR = 1/\left(\frac{1}{r_p{}^2} + \frac{1}{r_b}\right) \quad (1)$$

B. Decompression phase.

Once that the multispectral image and the low resolution hyperspectral image have been received, the original image can be reconstructed by fusing the received images using one of the aforementioned fusion algorithms. The accuracy of the results obtain will depend on the fusion algorithm selected.

C. Advantages of this methodology.

Using this method for compressing and decompressing hyperspectral images, the compression process is pretty simple, being the decompression process the tricky one. This fact represents an important advantage with respect to the state-of-the art methodologies, since the compression process, which must be performed onboard, is typically much more complex than the decompression process. One extra advantage of the proposed method is that the development of new fusion algorithms which produce better results than the state-of-the-art algorithms for this task will passively improve the compression results obtained.

III. METHODOLOGY BASED ON ORTHOGONAL PROJECTION

The FUN algorithm which was develop for linearly unmix hyperspectral images, is able to extract the pure spectral signatures present in a hyperspectral image based on orthogonal projections using the Modified Gram-Schmidt method. This algorithm does not perform complex matrix operations, can be easily parallelized and is very computational efficient compare with other unmixing algorithms. This algorithm has been slightly simplified within this work in order to extract just the orthogonal vectors used in the unmixing process. The stopping criteria has also been modified to stop the orthogonal vectors extraction when a certain number of vectors, n_{pv}, has been extracted, in order to achieve a certain compression ratio or a certain signal-to-noise ratio (SNR) in the compression-decompression process. Once that the orthogonal vectors have been extracted, they are used to project the image to be compressed into the space spammed by these vectors. This way, a projected image, which is much smaller than the original one, is obtain. This new image and the projection vectors can now be transfer to the earth. The original image can be reconstructed as the product of the projected image and the projections vectors.

A. Stopping condition based on the compresion ratio.

The dimension of the projected image is directly related to the dimension of the image to be compressed and the number of projection vectors extracted. Hence, the number of vectors to be extracted, n_{pv}, can be easily fixed in advance in order to obtain a desire compression ratio.

B. Stopping condition based on the SNR.

The FUN algorithm sequentially extracts the aforementioned orthogonal vectors which are used to project the image to be compressed. Each time that one of these vectors is extracted, the information of the image that can be spammed by this vector is subtracted of the image. Hence, the remaining information is the information which cannot be spammed by the projections vectors extracted and is directly related with the losses of the compression-decompression process. Due to this reason, once that a projection vector is extracted and the information that this projection vector can spam is subtracted from the image to be compressed, the remaining information is evaluated. This way, the algorithm can be stop if the information lost allows the achievement of a predefined desirable SNR.

C. Advantages of this methodology.

This method presents many important advantages. First of all, this algorithm allows the definition of a certain compression ratio and SNR to be achieve in the compression-decompression process. Secondly, the algorithm is computational efficient, easily to parallelized and does not perform complex matrix operations. Moreover, the algorithm can be independently applied to macroblocks of the image, obtaining even better results that applying it to the entire image. Moreover, the image can be processed by bands or by pixels, without performing any modification to the algorithm, which allows to use this method for sensor which provides data in BSQ and BIP formats. As an extra advantage of this methodology which clearly distinguish it from the state-of-the-art methods is the fact that the compression-decompression process using the FUN algorithm remove noise from the image to be compressed, which clearly benefits the hyperspectral and ultraspectral data analysis.

IV. RESULTS

Some simulations have been performed in this work, using real images collected by different sensors, in order to verify the goodness of our proposal. Moreover, the same images has also be compressed and decompressed using the Lossy Compression for Exomars (LCE) [7] method, which provides very good compression results for most situations and is one of the most important state-of-the-art algorithms for this task. In particular, three different images have been used, collected by the AVIRIS, AIRS and CRISM sensors. These images have an spatial resolution of 512x677, 135x90, 480x320 pixels and 224, 1501 and 545 spectral bands respectively. The goodness of the different compression methods has been evaluated attending to the SNR achieved by these algorithms at different compression ratios. The Figure 1 shows the values of the SNR obtained with the different methods using the AVIRIS, AIRS and CRISM image respectively. The compression ratio is represented in bits per pixel per band (bpppb). Labels CDF and CFUN refers to the proposed methodologies, based on data fusion algorithms and based on the FUN algorithm, respectively.

According to the results obtain it can be conclude that the method based on orthogonal projections that has been proposed usually provides the best results for high compression ratios, while the LCE algorithm provides the best results for small compression ratios. The method based on data fusion has been tested using the CoEf-MHI fusion algorithms, however, the used of another fusion algorithm could provide different results. This method provides worse results than the other two evaluated methods. Its main advantage is that it is able to provide good SNR for acceptable compression ratio with drastically less computational complexity.

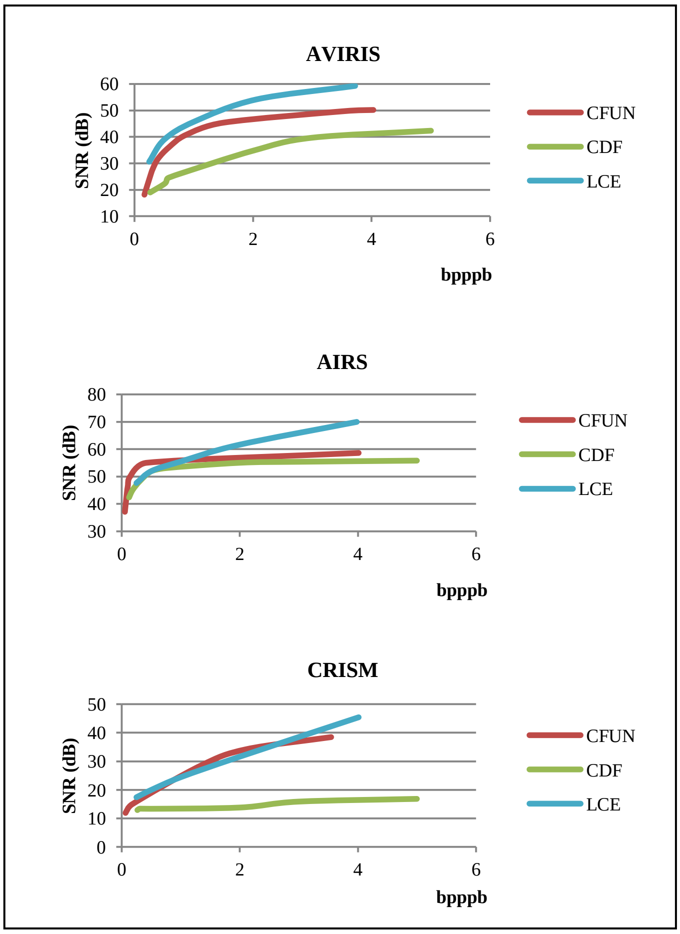

Figure 1. Compression results obtained for different images and different compression ratios, using LCE compresor and the proposed methodologies.

V. CONCLUSIONS

Two new methodologies for onboard compressing hypserspectral images have been proposed in this work. One of the proposed methodologies is based on data fusion. The main advantage of this methodology is that the compression process, which is performed onboard, is drastically much simpler than the state-of-the-art algorithms for this task. The second methodology proposed is based on the FUN algorithm. This method is also hardware-friendly and computational efficient. Moreover, it can be applied to macroblocks or to the entire image, providing similar results in both situations. It is able to compress the image by bands or by pixels, without performing any modification in the algorithm, which allows this algorithm to get easily adapted to sensors which provides data in BIP or BSQ format. Moreover this algorithm removes noise from the hyperspectral image to be compressed, which represents an important advantage for the hyperspectral image analysis.

In order to verify the goodness of our proposal some simulations have been performed, using different hyperspectral data acquired by different sensors. In order to compare the results obtained these images have also been compressed and decompressed using the Lossy Compression for Exomars (LCE) algorithm, which provides very good compression results for most situations and is one of the most important state-of-the-art algorithms for this task. According to the results obtained it can be concluded that the LCE and the proposed method based on the FUN algorithms provide similar results. The results provided by the method based on the FUN algorithm tends to be better than the results provided by the LCE algorithm for high compression ratios, while they are worse for smaller compression ratios. The proposed methodology based on data fusion provides worse results than the other two methods, however, it provides decent SNR for acceptable compression ratio with a drastically less computational complexity.

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