INTRODUCTION

Hyperspectral sensors are well suited for the analysis of water composition for the spatial resolution can be limited in coastal area. Hyperspectral high spatial resolution imaging satellite (with only 4 spectral bands) can be used to improve the spatial resolution of hyperspectral sensors.

Due to technical limitation, no satellite sensor is able to provide hyperspectral image with a spatial resolution. The image fusion which is the process of combining information from different sensors will allow to have a “perfect” image that would be acquired by a “perfect” sensor (high spatial and spectral resolutions).

ARSIS

The ARSIS concept uses the multisresolution analysis. The missing information of the high spectral image by using the details obtained from a high spatial resolution image. The latter decomposed from fine to coarse resolution schematized by a Laplacian pyramid as below

1. The convolution of the high spatial resolution image (multispectral - A) with a kernel allows to calculate the successive approximations and the details (step 1).
2. The same procedure is applied to the low spatial resolution (hyperspectral- B) (step 2).
3. At the lowest resolution level, the approximations of the 2 images are used to obtain the parameters of the Inter Modality Model (IMM) (step 3).
4. From the IMM, the inverse transform is derived (step 4).
5. Then the inversion of the hierarchical tool for the structures description allowing the synthesis of the image B with the spatial resolution of A (step 5).

\[ Y_{W} = X_{H} \]

The high spatial resolution image is derived with the multispectral data. Where Y is the high spatial resolution image with the fusion data, X is the multispectral data, and \( H \) the spatial scaling transform matrix.

\[ Y_{W} = X_{H} \] \[ X = W_{H} \] \[ W_{H} = Y_{W} H_{X} \]

The ARSIS output can be derived from the fusion of high spatial resolution image with the multispectral information. The spatial scaling matrix, therefore, the spatial transform matrix is derived from the fusion of high spatial resolution image with the multispectral data.

THE METHOD

The Nonnegative Matrix Factorization (NMF) is the way to decompose nonnegative data into 2 nonnegative matrices [9]. The Coupled Nonnegative Matrix Factorization (CNMF) unmixing both hyperspectral and multispectral data, respectively into endmembers and abundance matrices based on linear mixture model.

Considering a linear spectral mixture model, a hyperspectral image \( X \) (a nonnegative data) can be decomposed into two nonnegative matrices \( W \) and \( H \).

\[ X = W H \]

\( W \) represents the matrix containing the spectral profile of the endmembers and \( H \) the matrix containing the abundance of each endmember.

The multispectral image \( Y \) can be decomposed as:

\[ W_{R} = R W_{X} \]
\[ H_{Y} = S H_{X} \]

Where \( R \) and \( S \) represent respectively the spectral response transform matrix and the spatial spread transform matrix.

A recursive procedure between eq.2 and eq.3 is operated until the objective function described below reaches a certain threshold defined by the user:

\[ \min \| X - W_{X} H_{Y} \|_{F} \]

The hyperspectral image with high spatial resolution is then obtained:

\[ Z = W_{X} H_{Y} \]

The detailed algorithm of the Coupled Non-negative Matrix Factorization can be found in [4, 5].

RESULTS

Input images (hyperspectral and multispectral) as well as the reference image have been generated from the Hyperspectral Imagery for Coastal Ocean (HICO) image and the fusion resulting image were then compared with the reference one. Furthermore, the resulting fusion images are used in order to estimate the biophysical parameter such as: chlorophyll, yellow substance, suspended matter and bathymetry as represented in fig. 4.

Fig 1: The algorithm of the ARSIS implementation [2].

Fig 2: Simulated image (a) and (b) representing the hyperspectral and the multispectral images, (c) the reference and (d, e) respectively the results from ARSIS and CNMF methods.

Fig 3 Spectral profiles extracted from the fusion images resulting from the 2 methods (ARSIS and CNMF) and the reference: vegetation (a), lagoon (b) and sea (c).

Fig 4: Estimation maps from the inversion of Lee’s model, (b) yellow substance (m-1), (c) suspended matter (g/m3) and (d) bathymetry (m). (a) chlorophyll (mg/m3). Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>ARSIS</th>
<th>CNMF</th>
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<tbody>
<tr>
<td>CH (mg/m3)</td>
<td>0.26</td>
<td>0.23</td>
</tr>
<tr>
<td>SM (mg/m3)</td>
<td>7.55</td>
<td>1.76</td>
</tr>
<tr>
<td>YS (m-1)</td>
<td>0.17</td>
<td>0.17</td>
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<tr>
<td>Bathymetry (m)</td>
<td>16.88</td>
<td>16.74</td>
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Tables: (left) Statistical parameters (best results in bold), (right) Root Mean Square Error calculated from the maps (best results in bold).

Conclusion

The results show that the CNMF method performs better than the ARSIS for the fusion of hyperspectral and multispectral image according to statistical parameters and biophysical parameters. In a previous works, we showed that ARSIS performs better than the CNMF method for the fusion of 2 multispectral images like 52 and 93.

Compared to ARSIS, the CNMF method requires an optimization step to find the optimal number of endmembers. ARSIS is also less time consuming than CNMF.

REFERENCES