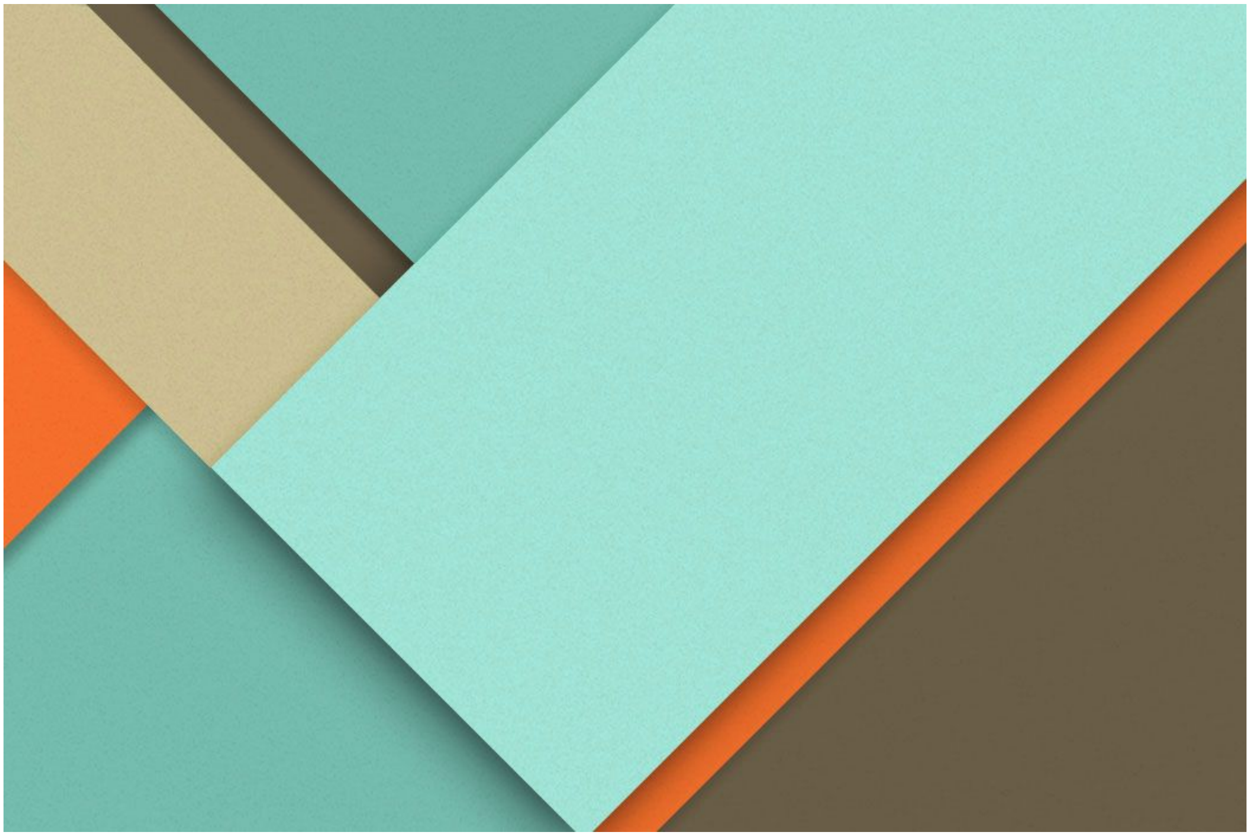

A NEW SATELLITE IMAGE FUSION METHOD BASED ON DISTRIBUTED COMPRESSED SENSING

Project 36

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Introduction

Satellite imaging is a vital topic to obtain high-resolution images of observed target. Usually, satellite imaging sensors include **multispectral (MS) sensors** and **panchromatic (PAN) sensors**.

- Low Resolution Multispectral Image :

  Due to constraints of received energy and physics of sensors, the **multispectral image** detected by multispectral sensors is of **high spectral resolution** and **low spatial resolution**, named as LRM image.

- High-Resolution Panchromatic Image :

  In the case of PAN image detected by PAN sensors is of **low spectral resolution and high spatial resolution**, named as HRP image(High-Resolution Panchromatic).

Problem Statement

The problem statement is to generate an HRM image (High-Resolution Multispectral) to **optimally benefit from** the advantages of the LRM image (that has a high spectral resolution) and the also HRP image (that has a high spatial resolution).

This image fusion procedure, which is known as **pan-sharpening** or **intensity substitution.**

Motivation

- Pan Sharpening can play an important role in Computer Vision. Many tasks in Computer Vision such as object detection and information retrieval in satellite images can see improved performance if we perform pansharpening on the image as a pre-processing step as this provides rich surface information.
- Object-based image analysis and Information Retrieval require very high-resolution images to extract the objects of interest and useful information

about them. Hence both the spatial and spectral properties matter. Hence using Pan Sharpening can give better results in these areas.

- Pan Sharpening also helps to high-quality images from the satellite. Satellites cannot give these high-quality images directly due to constraints of received energy and physics of sensors.
    - **Multi-spectral sensors** will typically sample over a larger spatial extent to get the necessary amount of energy needed to 'fill' the imaging detector. This results in a coarser image with high spectral characteristics with the compromise on spatial characteristics.
    - **Panchromatic sensors** on the other hand sample over a smaller spatial extent to get a pan image which has high spatial characteristics with a compromise on spectral characteristics.
    - Hence combining both of these we get a high-quality image with both spatial and spectral characteristics.

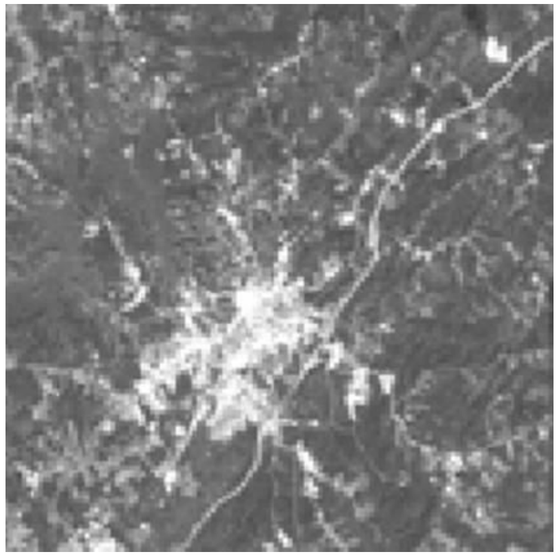
Overview

Input

The inputs that will be taken are an LRM image and a corresponding HRP image

Sample LRM image

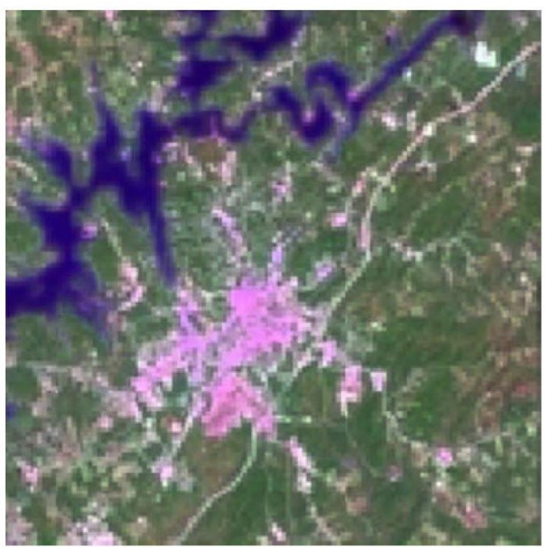
Sample HRP image



Output

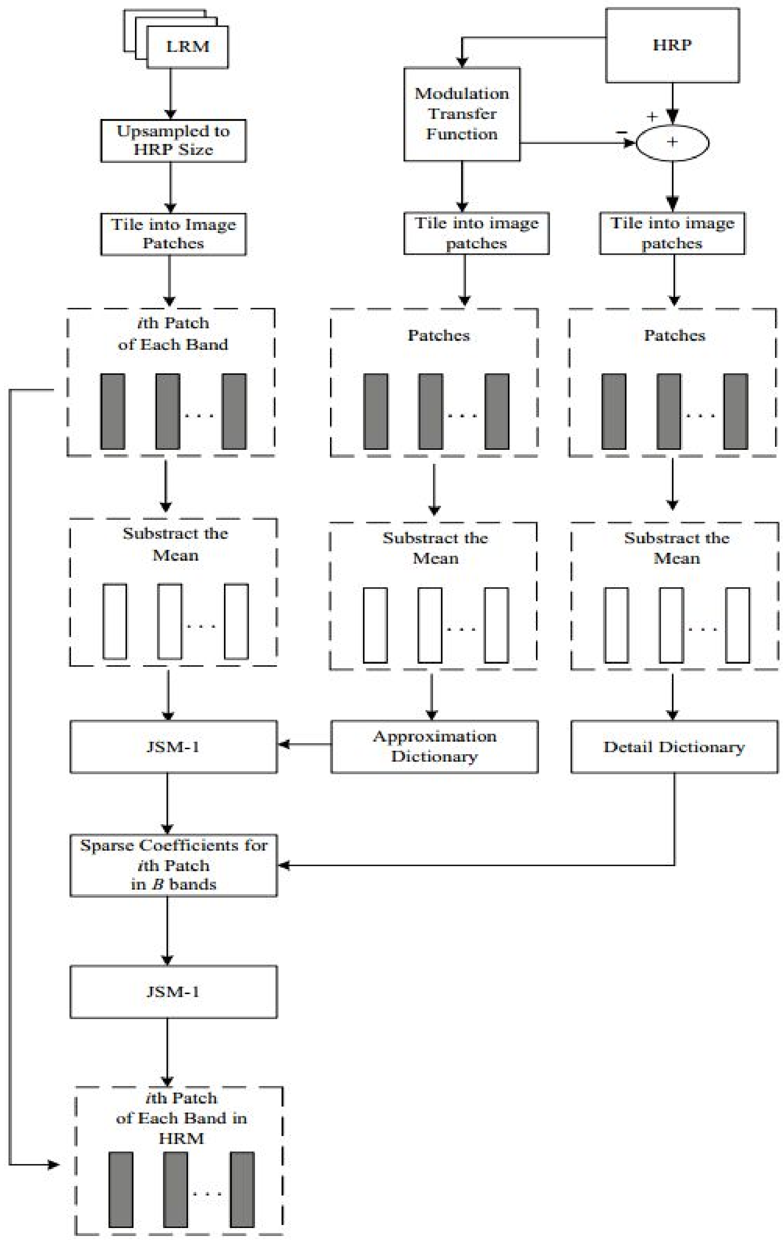
The output will HRM image which is the pan-sharpened version of the input LRM

Sample Output



The pipeline of the Method Proposed

This is the overall flow diagram of our implementation



Using the HRP image we compute the Dapp and Ddet dictionaries. Then using the OMP Algorithm we get sparse coefficients. Using these we add the details to the LRM image resulting in the HRM image.

Approaches considered

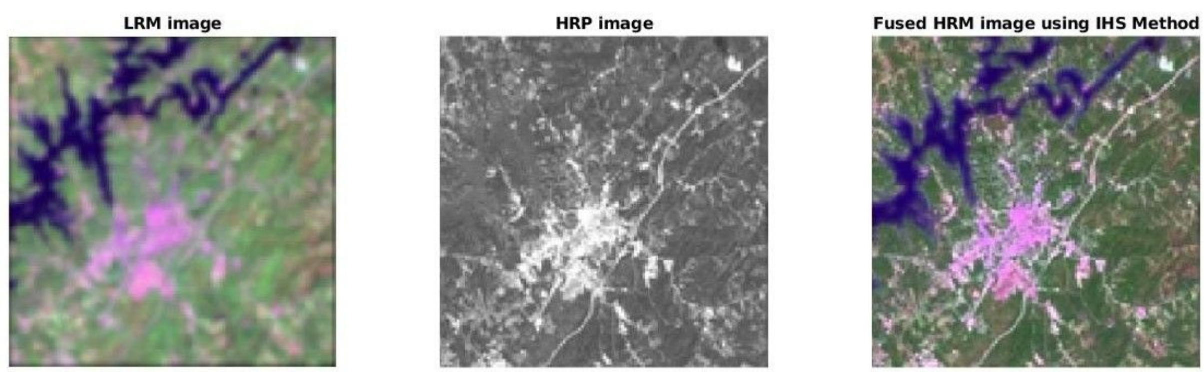
- Initially, we had planned to build a two models/prototypes using the two methods below so that we can get an idea of output that is to be generated.
- We have also used these two models to compare the results that we got through the implementation of the paper.

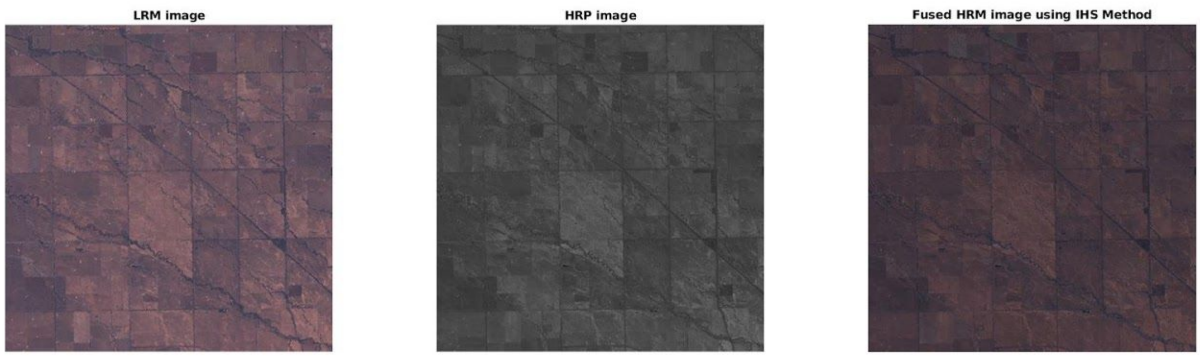
RGB to IHS transformation

A simple and commonly used approach to fuse multispectral and panchromatic images is the RGB -IHS color space forward and inverse transformation technique.

- First, we transform the given image into **IHS color space**.
- This transformation enables a replacement of the “**intensity component**” of the IHS transform (which is derived from the multispectral image) to be **replaced by the high spatial resolution panchromatic image**.

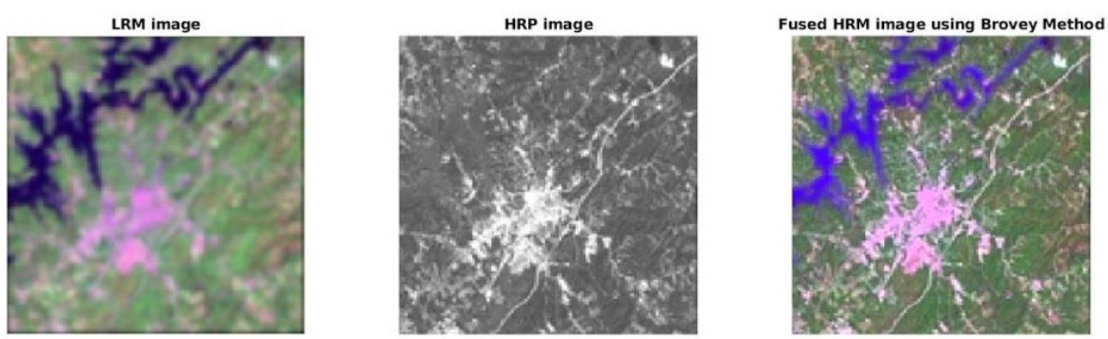
- This new intensity image, together with the original hue and saturation images (from the multispectral image) are then transformed back into an RGB color space for visualization

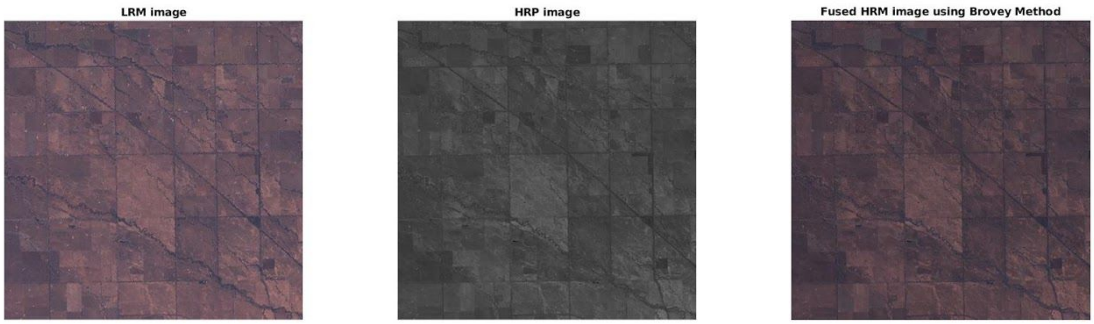




Brovey method

- This method is based on the **chromaticity transform**. It is a simple method for combining data from multiple sensors with the limitation that only three bands are involved.
- In this method, we **normalize the three multispectral bands** used for RGB display and to multiply the result by any other desired data to **add the intensity or brightness component to the image.**





Why is the proposed method better

- All the methods mentioned above tend to utilize the spatial resolution of HRP image but cannot keep the spectral characteristics of the original LRM image. These methods are called component-substitution methods.
- Compressed-sensing based fusion methods, on the other hand, are capable of making better use of the high spectral resolution in LRM image and high spatial resolution in HRP image.
- The proposed method in the paper **uses distributed compressed sensing** to give better results than compressed sensing.
- **It uses Joint Sparsity Model(JSM-1) to preserve the inter-signal correlation**.

Proposed Method in the paper

In this method, we use the Distributed compressed sensing theory (DCS)

What is DCS :

In Distributed Compressed Sensing we try to get the K-sparse signal x from a signal y where y and x are related as y = M*x. Here rank of the observation matrix M is not full that is general methods in linear algebra are not applicable. Hence algorithms like OMP are used to estimate x. Then this sparse representation x is sent to the user who can get back y using M*x.

$$\begin{bmatrix} {y_1}^i \\ {y_2}^i \\ \vdots \\ {y_B}^i \end{bmatrix} = \mathbf{M} \begin{bmatrix} {\mathbf{x}_1}^i \\ {\mathbf{x}_2}^i \\ \vdots \\ {\mathbf{x}_B}^i \end{bmatrix}$$

Algorithm:

- First, we get the low pass version of the HRP image by using a Gaussian on the FFT of the image.

  Assumption: To get the low pass version of the HRP image we actually have to use the **MTF function of the PAN sensor,** but as we **do not have information** about it, we alternatively used Gaussian to get the low pass image.

  Because of this, we have a parameter that is the **standard deviation of the Gaussian,** this has **to be fine tuned to get better results**.

- Now we compute the dictionaries called Dapp and Ddet .
- **Dapp** is obtained by tiling the low pass version of the LRM image into **tiles of size KxK with r% overlap**. Mean is subtracted from each tile to center the pixels.
- Ddet is obtained by repeating the same process of the high pass version of the LRM image. The high pass version can be obtained by subtracting the low pass version from the image.
- Then we compute the observation matrix M.
- Then the DApp is computed by properly arranging the earlier obtained Dapp dictionaries.

$$\text{DApp} = \begin{bmatrix} \mathbf{D}_{app} & \mathbf{D}_{app} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{D}_{app} & \mathbf{0} & \mathbf{D}_{app} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{D}_{app} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{D}_{app} \end{bmatrix}$$

- Similarly, Ddet matrix is computed using Ddet dictionaries in the same format as above.
- Then LRM image upsampled to the size of the PAN image. Then we model LRM image patches using JSM-1 (joint sparsity model).

$$
\begin{bmatrix} \mathbf{x}_1{}^i \\ \mathbf{x}_2{}^i \\ \vdots \\ \mathbf{x}_B{}^i \end{bmatrix} = \begin{bmatrix} \mathbf{D}_{app} & \mathbf{D}_{app} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{D}_{app} & \mathbf{0} & \mathbf{D}_{app} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{D}_{app} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{D}_{app} \end{bmatrix} \begin{bmatrix} \alpha_c{}^i \\ \alpha_1{}^i \\ \vdots \\ \alpha_B{}^i \end{bmatrix}
$$

- Now using the OMP Algorithm the sparse coefficient (alpha) for each patch in the images are estimated.

$$
\begin{bmatrix} y_1{}^i \\ y_2{}^i \\ \vdots \\ y_B{}^i \end{bmatrix} = \mathbf{M} \begin{bmatrix} \mathbf{x}_1{}^i \\ \mathbf{x}_2{}^i \\ \vdots \\ \mathbf{x}_B{}^i \end{bmatrix} = \begin{bmatrix} \mathbf{M}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{M}_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{M}_B \end{bmatrix} \times
$$

$$
\begin{bmatrix} \mathbf{D}_{app} & \mathbf{D}_{app} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{D}_{app} & \mathbf{0} & \mathbf{D}_{app} & \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{D}_{app} & \mathbf{0} & \mathbf{0} & \cdots & \mathbf{D}_{app} \end{bmatrix} \begin{bmatrix} \alpha_c{}^i \\ \alpha_1{}^i \\ \vdots \\ \alpha_B{}^i \end{bmatrix}
$$

- Then using them we add the details to the LRM image patch(x) resulting in the HRM image patch(h).

$$
\mathbf{h}_k{}^i = \mathbf{x}_k{}^i + \mathbf{D}_{det} \alpha_k{}^i
$$

Work Performed :

Experiments :

Matrix M:

It has the structure :

$$\begin{bmatrix} \mathbf{M}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{M}_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{M}_B \end{bmatrix}$$

- The measurement matrix *M* must satisfy RIP of order *K*. Let M_t be the submatrix obtained by extracting the columns of *M* corresponding to the indices in *T*. Define the *K*-restricted isometry constant δ_K of *M* which is the smallest quantity such that for all subsets *T* with and all real coefficients.
- These two properties can be achieved with high probability simply by selecting *M* as a random matrix.
- Hence initialize each of the matrices M_i randomly.
- To generate these we have performed experiments using different types of distributions like Gaussian, Bernoulli etc for selecting the random numbers.
- Of these we found Gaussian to be the best.

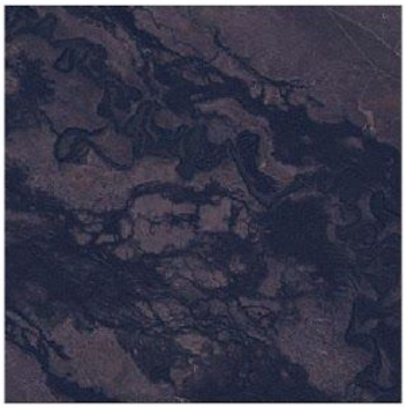
Datasets used :

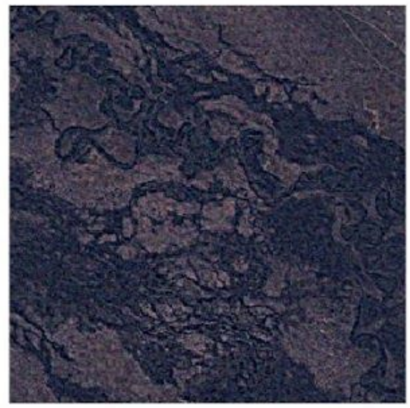
The datasets on which we tested and evaluated our algorithm are **Landsat** and **AOI_3_Paris_Roads_Test_Public.**

The Method has six parameters which are to be fine-tuned to get better results :

1) **The standard deviation of the Gaussian used to get the low pass image:**
    - In the paper given to us, the computation of low pass version of images was done using the **MTF(Modulo Transfer Function) of the PAN sensor.** But we did not have any information about it. Hence we **approximated** it using a

Gaussian function. The **standard deviation** of this Gaussian is taken as a **parameter**.





Standard deviation = 120   Standard deviation = 30

- We can clearly see that for lesser standard deviation the there is more noise, this is because edges are being overly added, this is because there is no smoothing done before addition.

2) Patch size
    - We had tried different patch sizes and found out that if the patch size is too small then the output image becomes blocky, and if it is too large then the details are not visible properly.
3) A number of iterations of the OMP Algorithm, Convergence condition based on the difference of residues.
    - The above two parameters decide how much detail is added to the LRM image, if the number of iterations is very less then the HRM image and the LRM image will almost be the same, on the other hand, if the number of iterations is very high then HRM image will become noisy.

Evaluation Metrics:

The Results are evaluated using **Wald's synthesis protocol** as proposed in the paper.

Here we take **original LRM image as the reference image** and compare it with the image obtained after **fusion of the decimated LRM and HRP images**.

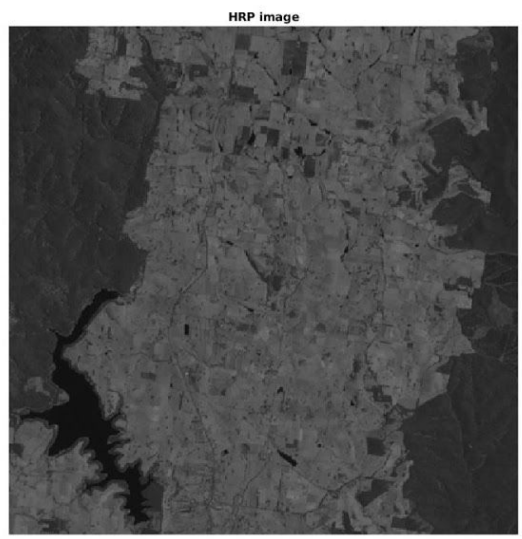
The fusion results are evaluated by

1) The Spectral Angle Mapper (SAM)
2) Erreur Relative Global Adimensionnelle de Synthese (ERGAS)
3) RMSE

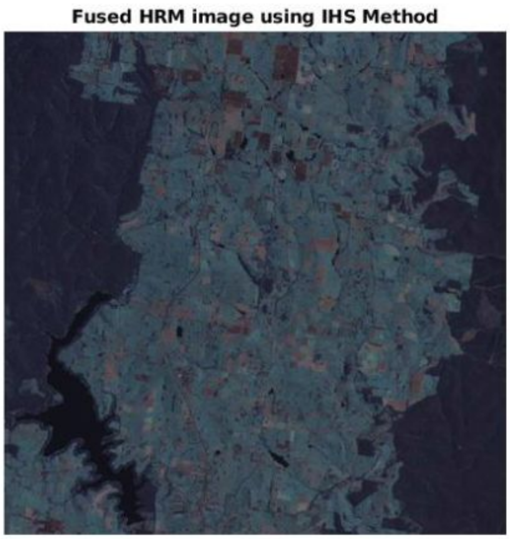
Results :

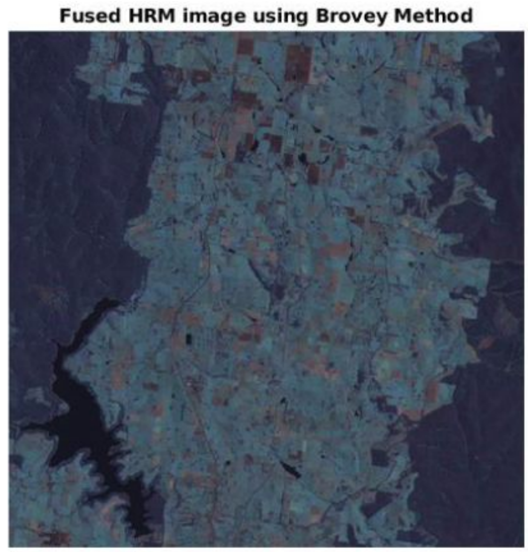
Successes :

Inputs

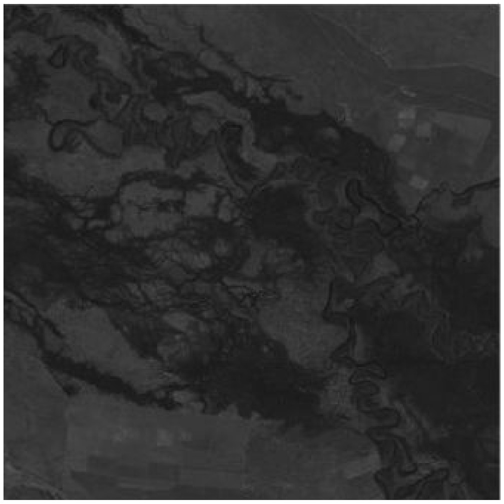


Outputs





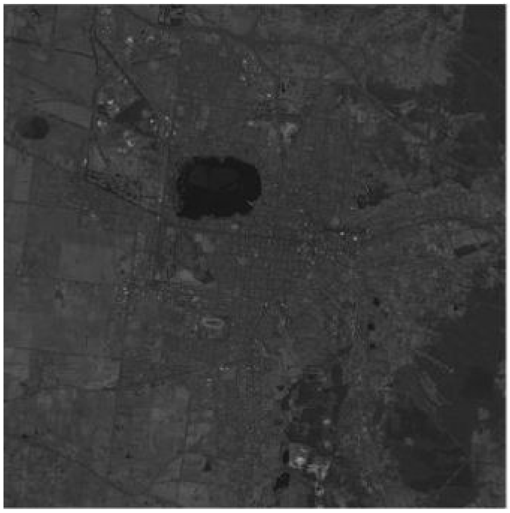
Proposed Method



Input PAN image

Input LRM image

Output HRM image

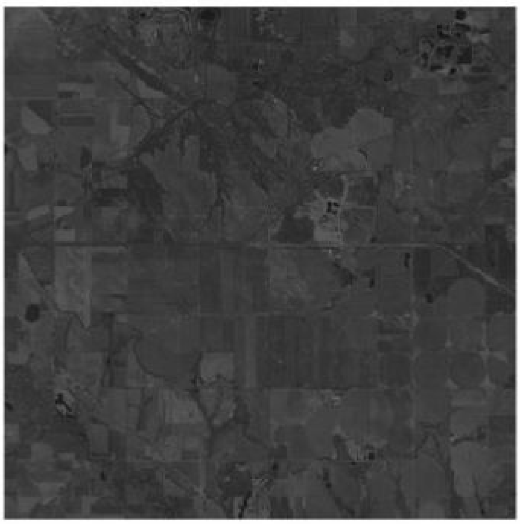


Input PAN image

Input LRM image

Output HRM image

Failures :



Input PAN image

Input LRM image

Output HRM image

- In this case, we can clearly see that even with the fine-tuned parameters the output HRM image is having a lot of noise. This might be because of our assumption that H can be modeled as the linear combination of image patches in P, w which might be failing in this case.

Values Obtained on different Evaluation Metric's.

	SAM	ERGAS	RMSE
IHS	1.2009	0.072005	0.087779
BROVEY	**1.1997**	0.056926	0.0699062
Proposed Method	1.3028	**0.028132**	**0.033685**

Github Link :

https://github.com/sakethkhandavalli/dip-project

Task Assignment :

Tasks	Pradeep	Saketh
Initial Prototype methods (IHS,Brovey)	90%	10%
Evaluation Metrics	10%	90%
Main Pipeline	60%	40%
Computing dictionaries	40%	60%
OMP Algorithm Implementation	30%	70%
Finding out output patches	50%	50%
Evaluate on Dataset and Compare the results	50%	50%

References :

[Fusion Method Based on DCS]

[Distributed Compressive Sensing]

[OMP Algorithm and compressive sensing basics (online course)]