Pipeline Method Using Optimized Gram-Schmidt and Iterative Weighted Brovey for Panchromatic Sharpening of Remote Sensing Images

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Abstract

Panchromatic sharpening of low-resolution multi-spectral images is crucial in the field of remote sensing in order to obtain clear and sharp high-resolution version of those images. The current state-of-the-art in panchromatic sharpening is learning-based methods. Although learning-based methods may provide high accuracy with sufficient training iterations, they often suffer from both lengthy training time and overfitting. Thus, it is desirable to have a panchromatic sharpening method that is able to perform well without lengthy training time and generalized enough for various cases. In order to achieve those goals, we look back into two component substitution techniques, which are Gram-Schmidt and Weighted Brovey. We propose the integration of those two techniques within a single pipeline with further tweaking for each individual part. In the Gram-Schmidt part, we utilize fast weight optimization to programmatically determine the optimal weights for the creation of the simulated panchromatic version of the input images. In the Weighted Brovey part, we run the algorithm in multiple iterations as the output of one iteration is multi-spectral images that can be further sharpened. By utilizing ERGAS evaluation, the proposed pipeline method shows better performance when compared with several baseline component substitution techniques with the score of 1.826.

1. Introduction

Panchromatic sharpening (pan-sharpening) refers to the use of a high-resolution panchromatic image to fuse with lower-resolution multi-spectral (e.g. red band, green band, blue band, etc.) images in order to produce multi-spectral images with the resolution of the panchromatic one. Generally, pan-sharpening methods are classified into several different families, which consist of component substitution (CS) family, multi-resolution analysis (MRA) family, and variational optimization (VO) family [4]. However, those aforementioned families are often considered to be classical methods, with many research nowadays focusing on the development of learning-based pan-sharpening methods utilizing neural networks. Examples of such pan-sharpening methods are PanNet [6] and PNN [3].

Despite the high accuracy of learning-based pan-sharpening methods, they are often hindered by excessively lengthy training time, with PanNet requiring 2.5×10^5 [6] and PNN requiring 1.12×10^6 [3] iterations to achieve convergence respectively. Besides, learning-based methods are inherently prone to overfitting, especially if the model is trained on a limited dataset with low variance between data. Those two problems could lead to difficuly in implementing such methods in a real-world setting.

In contrast, the aforementioned classical methods do not require training with dataset beforehand at all and as such, they are not vulnerable to overfitting. Based on those reasons, this report focuses on refining classical methods, specifically CS methods due to their simplicity and fast computation time. Empirical testing shows that Weighted Brovey and Gram-Schmidt achieve the lowest pan-sharpening error when compared to other methods in the CS family.

Therefore, the key contribution of this report is to propose a pipeline method called OGS-IWB Pipeline, which consists of Gram-Schmidt and Weighted Brovey parts, to pan-sharpen remote sensing images. Both of those parts are then further tweaked to improve the resulting high-resolution pan-sharpened images. Fast weight optimization is added to the Gram-Schmidt part to programmatically obtain optimal weights for producing simulated panchromatic image, which is then used to initialize the Gram-Schmidt transformation. Meanwhile, iterative computation is added to the Weighted Brovey part since the output of one iteration can be used as input images for the next iteration for further pan-sharpening.

2. Proposed Solution

2.1. Overview of the Pipeline Method

As can be seen on Fig. 1, the proposed pipeline model accepts high-resolution panchromatic image along with low-resolution multi-spectral images as its input. In this case, the multi-spectral images consist of 4 bands, which are near-infrared (NIR), red, green, and blue bands. Both high-resolution panchromatic image and low-resoluton multi-spectral images are then fused together using Optimized Gram-Schmidt (OGS) resulting in high-resolution multi-spectral images. The resulting high-resolution multi-spectral images from OGS are then fed into Iterative Weighted Brovey (IWB), which also requires the initial panchromatic image as its input. The output of the IWB is then fed back to the IWB itself for *i* iterations. At the end of the IWB iterations, we will obtain refined high-resolution multi-spectral images.

2.2. Optimized Gram-Schmidt

The original steps for computing the Gram-Schmidt transformation of the multi-spectral images can be seen in [2]. The OGS computation is needed to obtain the initial high-resolution multi-spectral images. The first step in OGS is to generate a simulated panchromatic image from the original panchromatic image. Note that in this step, the original panchromatic image should be downsampled to the resolution of the multi-spectral images first.

The equation needed to compute the simulated panchromatic image is given by Eq. (1).

$$PAN_{sim} = \sum_{i=1}^{T} w_i B_i \tag{1}$$

where PAN_{sim} is the simulated panchromatic image, T is the number of bands, w_i is the assigned weight for the i^{th} band, and B_i is the input image matrix for the i^{th} band. The equation to obtain the optimal w_i for Eq. (1) is given by Eq. (2)

$$W = \arg \min_{w_i \subset W} \frac{1}{N \times M} \sum_{j=1}^{N} \sum_{k=1}^{M} (PAN_{down_{(j,k)}} - \sum_{i=1}^{T} w_i B_{i_{(j,k)}})^2 \tag{2}$$

where W is a set of w_i under optimization, N and M are the width and height resolution in pixels respectively, and PAN_{down} is the downsampled original panchromatic image. The optimization is solved using Nelder-Mead algorithm for fast computation [5]. The main objective of this optimization is to minimize the mean-squared error between the simulated panchromatic image and the downsampled original panchromatic image.

Afterwards, the matrix of each band will be considered as multi-dimensional vector to be orthogonalized against each other using Gram-Schmidt transformation. In this orthogonalization process, the Gram-Schmidt (GS) matrix for each band is calculated from the previous $i-1$ bands with PAN_{sim} initialized as GS_1. The transformation of input bands to GS matrices is given by Eq. (3).

$$GS_i = (B_i - \mu_i) - \sum_{l-1}^{i-1} \frac{B_i \cdot GS_l}{\|GS_l\|^2} GS_l \tag{3}$$

where μ_i is the mean of the matrix of the i^{th} band.

The original panchromatic image is then gain and bias-adjusted against PAN_{sim} to generate an adjusted high-resolution panchromatic image (PAN_{adj}). The equation to obtain gain and bias are given by Eq. (4) and Eq. (5) respectively, while the equation to obtain PAN_{adj} is given by Eq. (6).

$$Gain = \frac{\sigma PAN_{sim}}{\sigma PAN} \tag{4}$$

$$Bias = \mu PAN_{sim} - \mu PAN \times Gain \tag{5}$$

$$PAN_{adj} = PAN \times Gain + Bias \tag{6}$$

where σ is the standard deviation operator, μ is the mean operator, and PAN is the original panchromatic image.

The aforementioned GS_1 is then changed to the obtained PAN_{adj}. Afterwards, inverse Gram-Schmidt transformation is computed to obtain the high-resolution multi-spectral images. The inverse Gram-Schmidt transformation equation is given by Eq. (7).

$$B_{out_i} = (GS_i + \mu_{up_i}) + \sum_{l-1}^{i-1} \frac{B_{up_i} \cdot GS_l}{\|GS_l\|^2} GS_l \tag{7}$$

where B_{out_i} is the resulting high-resolution version of the i^{th} band, μ_{up_i} is the mean of the upsampled version of the i^{th} input band, and B_{up_i} is the upsampled version of the i^{th} input band. Therefore, high-resolution multi-spectral images can be obtained using OGS. The implementation of OGS in Python 3 can be seen in the following link: https://colab.research.google.com/drive/1JrNBU0-3yqoH_gFXwQCnpGzVO4SmNbMO?usp=sharing.

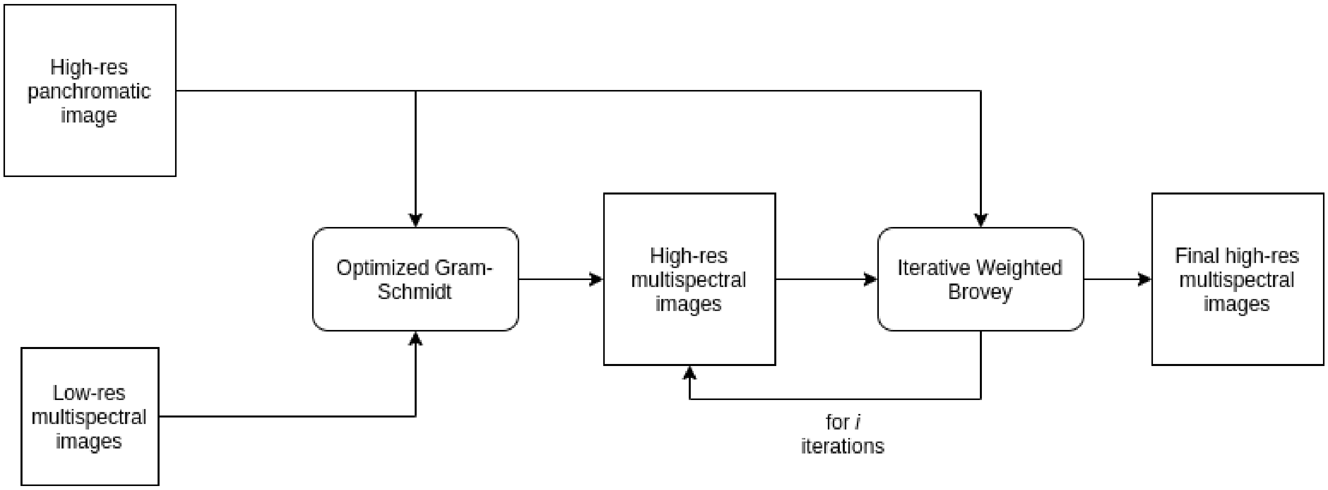

Figure 1. Architecture of the proposed pipeline model utilizing Optimized Gram-Schmidt and Iterative Weighted Brovey part (OGS-IWB Pipeline).

2.3. Iterative Weighted Brovey

Weighted Brovey transformation is used to increase the visual contrast in the low and high ends of the histogram of the images by taking into account the respective weights of each band [1]. In this transformation, DNF filter is first computed as given in Eq. (8).

$$DNF = \frac{PAN - w_{nir}B_{nir}}{w_{red}B_{red} + w_{green}B_{green} + w_{blue}B_{blue}} \quad (8)$$

where PAN is the original panchromatic image. w_{nir}, w_{red}, w_{green}, w_{blue} are the weights assigned to each corresponding bands with the values determined empirically. B_{nir}, B_{red}, B_{green}, B_{blue} are the input bands to be transformed.

The resulting DNF filter is then applied to the input bands to transform them to refined multi-spectral images. The application of the filter is given by Eq. (9).

$$B_{out_i} = B_i DNF \quad (9)$$

where B_{out_i} is the refined output of the i^{th} band and B_i is the i^{th} input band.

The Weighted Brovey transformation can then be run iteratively as shown in Algorithm 1. The number of the iterations is determined empirically. At the end of the iterations, IWB will generate refined high-resolution multi-spectral images. The implementation of IWB in Python 3 can be seen in the following link: https://colab.research.google.com/drive/1TtqYlvk2DWS3sW2_ic7XVhM8Jd7MaZu5?usp=sharing

Algorithm 1 Iterative Weighted Brovey (IWB) transformation

Require: $N > 0$
  $n \leftarrow 0$
  $B \leftarrow bands_{input}$
  while $n < N$ **do**
    $DNF \leftarrow Eq.$ (8)
    $B \leftarrow Eq.$ (9)
    $n \leftarrow n + 1$
  end while

3. Experiments

The proposed pipeline method (OGS-IWB pipeline) is evaluated using ERGAS on a panchromatic image and a multi-spectral image containing 4 bands, which are near-infrared (NIR), red, green, and blue bands. The resolution of the panchromatic image used for evaluation is 1200 $\times$ 1200 pixels, while the resolution of the multi-spectral image is 300 $\times$ 300 pixels. The format of the images used is unsigned integer 16-bit (uint16) TIFF. In the IWB part of the pipeline, we assign an equal weight value of 0.25 for each w_{nir}, w_{red}, w_{green}, w_{blue} respectively. Besides, we set the number of iterations (N) at 2 iterations.

The proposed method is then compared with a slew of other CS methods, such as: standalone Gram-Schmidt (standalone GS), standalone Weighted Brovey (standalone WB), and Esri. The result of the comparative evaluation can be seen on Table 1. Comparative evaluation using ERGAS clearly shows that the OGS-IWB pipeline offers the best pan-sharpening accuracy when compared with other CS methods.

Table 1. Comparative evaluation using ERGAS

Methods	ERGAS
Standalone GS	1.859
Standalone WB	2.524
Esri	3.199
OGS-IWB Pipeline	**1.826**
Ideal value	0

4. Discussion

The main challenge during the implementation of the proposed OGS-IWB pipeline is determining two parameter in the IWB part, which are the weight value for DNF computation and the number of iterations. As of the writing of this report, methods to numerically determine those parameter have not been formulated yet. Therefore, we recommend using empirical testing to determine the value of those parameter by manually observing and comparing the quality of the final pan-sharpened images when different parameter value is set.

During empirical testing to determine a satisfactory set of paramater, we find that as the weight value for DNF increasingly diverge from the most satisfactory one, more artifacts will appear on the final pan-sharpened images. Such artifacts are white pixels that appear throughout the pan-sharpened images. The number of those white pixels will also increase if the number of iterations exceed the most satisfactory one.

The main reason for the appearance of white pixels is probably because the value of some pixels within the image matrices exceed the 16-bit limit imposed by the image format. As previously mentioned in Sec. 3, the image format used in the evaluation is unsigned integer 16-bit. Therefore, if the integer value of a pixel exceeds that 16-bit limit, the pixel will manifest itself as a white pixel / dot on the image. By comparing the number of white pixels on pan-sharpened images when different parameter value is set, the most satisfactory parameter value can be empirically determined.

5. Conclusion and Future Work

In this report, we propose a pipeline method to pan-sharpen images utilizing Optimized Gram-Schmidt and Iterative Weighted Brovey, which we call OGS-IWB Pipeline. Optimized Gram-Schmidt utilizes programmatic weight optimization to generate a simulated pan-sharpened image that is as close as possible to the downsampled original panchromatic image. The resulting simulated pan-sharpened image is then used for Gram-Schmidt orthogonalization. Meanwhile, Iterative Weighted Brovey introduces iteration to Weighted Brovey transformation to generate a refined high-resolution multi-spectral images. Finally, both OGS and IWB are connected within a single pipeline to improve the overall quality of the pan-sharpened images. Comparative evaluation using ERGAS shows that OGS-IWB Pipeline achieves better performance than other CS methods.

For future work, we recommend two things to improve the proposed OGS-IWB Pipeline. First, the performance of the proposed OGS-IWB pipeline can be compared to other families of pan-sharpening methods, such as MRA, VO, and learning-based. Second, numerical methods to determine the parameter in the IWB part, which consists of weight value for DNF computation and the number of iterations, should be developed. Therefore, a more generalized OGS-IWB Pipeline model that is more applicable in real-life settings could be achieved.

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