**Datacube Preprocessing: Multitemporal Cross-Sensor Image Normalization**

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ABSTRACT:

Multitemporal cross-sensor imagery provides fundamental data for Earth's surface monitoring over time. However, analyzing these images is a challenging task. Visual inconsistencies are often found in these images due to atmospheric and surface conditions variations. Hence image normalization in image pre-processing is considered to minimize the errors due to inconsistencies. There are several normalization methods that have been developed, such as histogram matching and linear regression by iteratively reweighted multivariate alteration detection (IR-MAD). Despite that, these methods have limitations in preserving important features and require a reference image that may not be available or adequately represent the target images. To address those limitations this study was conducted, a relaxation-based algorithm is proposed for Multitemporal cross-sensor satellite image normalization. This algorithm iteratively adjusts the radiometric values of images using a relaxation process. The effectiveness of this method was evaluated on multitemporal cross-sensor image datasets and showed significant improvements in radiometric consistency compared to other methods. The proposed relaxation algorithm outperformed IR-MAD and the original images in reducing radiometric inconsistencies, maintaining essential features, and improving the accuracy (MAE = 3.8; RMSE = 4.6) and consistency of surface reflectance values (R2 = 94.01%).

1. **Introduction**

The application of the Multitemporal cross-sensor imagery has become increasingly for the analysis of changes and trends on earth’s surfaces (Gan et al., 2021). One of the challenges of the application of using the multitemporal cross-sensor images is the variations of atmosphere and surface conditions which affect the image consistency, specifically visual and radiometric value consistency. This inconsistency may lead to errors in analysis and misinterpretation of the results (Hemingway & Frazier, 2021). To overcome the issue, this study proposed a relaxation algorithm that improves image consistency without relying on a reference image. This algorithm iteratively adjusts the radiometric values of the images until desired level of image consistency is reached, which indicated by minimum error value between the multitemporal cross-sensor images. This relaxation algorithm was tested on multitemporal cross sensor image datasets that consist of Landsat 8 OLI images and Sentinel 2 MSI images that will be explained in section 2. Then, the results and discussion in section 3. Lastly, section 4 is the conclusion of this study.

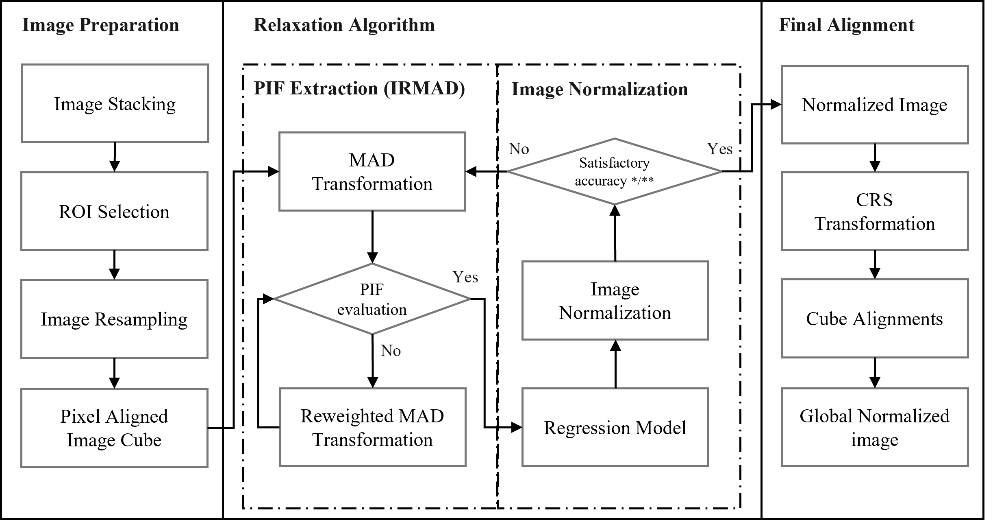
1. **Data and Method**
   1. **Satellite Data**

In this study we utilized a collection of multitemporal cross-sensor images from two sensor, Landsat 8 OLI (LANDSAT/LC08/C02/T1\_L2) and Sentinel 2 MSI (COPERNICUS/S2\_SR) surface reflectance images. Detailed information about each dataset can be found in Table 1. All available spectral bands (BLUE, GREEN, RED, NIR, SWIR1 and SWIR2) are used for analysis, except for the thermal, cirrus, and panchromatic bands. By examining these diverse datasets, we were able to gain valuable insights into the specific impacts of our proposed relaxation method on various geographic features.

**Table 1.** Multitemporal cross-sensor datasets were used in this study.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Dataset** | **Location** | **Acquisition date** | **Geographical features** | **Total Image** |
| #1 | Mut, Egypt | Oct – Dec 2020 | Small village in desert area | 6 |
| #2 | Manaus, Brazil | June – Sept 2021 | Cloud Pixels and urban area | 6 |
| #3 | Legrena, Greece | May – June 2022 | Water body, hill, and shadow | 6 |
| #4 | Nashville, USA | Sept – Oct 2022 | Seasonal affected urban area | 6 |

* 1. **Relaxation method Overview**

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**Figure 1.** Workflow of image normalization with relaxation algorithm

Figure 1 illustrates the workflow of the proposed relaxation algorithm for multitemporal cross-sensor image normalization. There are three stages in this workflow, the first stage is image preparation. At this stage we prepare all suitable images for further processing. After collecting all the satellite images at the specific location, we select the region of interest (ROI) to guarantee uniformity in terms of area and object perspectives across the images. Subsequently, image resampling is applied, involving the reduction of Sentinel 2 images' spatial resolution to 30 meters. This step to ensure compatibility with Landsat 8 images, which have a lower spatial resolution. Finally, the image preparation stage is ended with pixel-aligned image cube, where the images are aligned according to their pixels. The second stage is relaxation algorithm where this stage consists of two main steps, PIF extraction and image normalization. Each of these steps is described in detail below. Finally, the last stage is cube alignments where all normalized images are aligned locally and globally to create a global normalized image cube.

1. **PIF Extraction**

Generally, Pseudo Invariant Features (PIFs) denote Earth's surface attributes that exhibit relatively consistent over time, and they can be used to normalize remote sensing data (Lin et al., 2019; Rayegani et al., 2021). Examples of PIFs urban regions, road networks, and barren terrain, all of which maintain consistent surface reflectance values across time. One of the most widely used methods PIFs selection using Iteratively Reweighted Multivariate Alteration Detection (IR-MAD)(Nielsen, 2007).

The relaxation algorithm in this study utilizes the IR-MAD method to select the PIFs from paired images before we normalized the images. The IR-MAD method measures the degree of change or deviations between two or more spectral bands in paired image through the MAD statistic value (Nielsen et al., 1998). This statistic is computed based on the covariance matrix of the bands, capturing the relationships between the spectral values. The first MAD component describes the highest deviations between the spectral bands, while the last MAD component describes the lowest deviations between them. Subsequently, pixels with low deviations will be remark as unchanged pixels or PIFs. To enhance the selection of pseudo-invariant features, the IR-MAD method incorporates an iterative reweighting process. This process assigns weights to the spectral bands based on their contributions to the MAD statistic. Through multiple iterations, the weights are updated, allowing the method to adaptively identify and prioritize the most reliable pseudo-invariant feature selection.

1. **Image Normalization**

The subsequent step is image normalization right after the selection of PIFs is successfully executed. This study applied the regression model that written as Eq. (1) to transform the radiometric condition of the target image (image ) into the radiometric condition of the reference image (image ) (Denaro & Lin, 2019; Sadeghi et al., 2017). This regression utilizes PIFs from previous stage to remove the pixels that are constantly changing such as clouds, water, and even vegetation in some cases.

|  |  |
| --- | --- |
|  | (1) |

where and are the slope and intercept of image to image , which is obtained from the following Eq. (2). In this equation, and denote the standard deviation values from PIFs images of and . Then, and represent the mean value of PIF images of and respectively.

|  |  |
| --- | --- |
| . | (2) |

The relaxation algorithm is applied to obtain consistent surface reflectance value of the normalized images. This algorithm minimizes or an error function by constructing a sequence of iterations that expressed in Eq. (3) (Ninin et al., 2015). The algorithm operates by starting with an initial value of normalization parameters (slope (α) and intercept (β) variables) from the previous normalization result and repeatedly updating them until a desired level of convergence is obtained. This proposed algorithm gradually aligns the radiometric values of the target image with those of any reference image This is achieved through iterative iterations of Pseudo invariant features (PIFs) extraction and image normalization steps, where the input images are the previously normalized images. As a result, a more coherent collection of images is obtained.

|  |  |
| --- | --- |
| , | (3) |

where, is error function in this study with the objective to obtain the minimum total error value of each image against other images in the dataset. Then and are the set of slope and intercept components of the normalization. These sets will be updated through a relaxation iteration process until the minimum error value is obtained. Then, represents the PIFs masked images that formulated in Eq. (4) and Eq. (5). These are masked images that have been generated using common PIFs, which is a selected PIFs that is shared among multiple images and can be obtained by combining multiple PIFs selection results.

|  |  |
| --- | --- |
| , | (4) |
|  | (5) |

1. **Experimental Results**
   1. **Qualitative Analysis**

Figure 2 presents the comparisons of normalization results for each dataset with their specific characteristics and features. Egypt dataset with their dessert features, Brazil dataset with clouds and urban features, Greece dataset with topography and water features, lastly United States of America dataset with their seasonal features. Our approach effectively minimized image inconsistencies in complex datasets, such as those with dessert, clouds, water, and seasonal changes, while preserving key features. However, it was observed that our relaxation algorithm was not able to preserve topographic features on Greece dataset as well as IR-MAD. Those topographic features may be lost during the normalization process, which can result in a decrease in contrast in the normalized images. Although our method could maintain seasonally affected pixels, there might still be inconsistencies indicating seasonal transitions in the images.



**Figure 2.** Visual comparison of the normalization results between original images, IR-MAD, and proposed relaxation algorithms

* 1. **Quantitative Analysis**
     1. **Comparison of Normalization Results Accuracy**

This study evaluates the discrepancy between normalized images using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics help determine the differences between the normalized images. A smaller value of MAE and RMSE indicates better alignment and similarity between the normalized images. Based on the data in Table 2, it can be observed that the MAE and RMSE values of the proposed relaxation algorithm are consistently lower than those of the original images and IR-MAD. This indicates that our proposed relaxation algorithm is a more effective normalization method in reducing image discrepancies and errors. In summary, the accuracy measurements demonstrate that our relaxation method outperforms traditional methods and can effectively improve image quality.

* + 1. **Comparison of Normalization Results Similarity**

This study assesses the degree of similarity between normalized images using the correlation coefficient (R2). A correlation coefficient close to 1 suggests that the normalized images are highly similar, while a correlation coefficient close to 0 indicates a low similarity between the images. The correlation measurements are presented in Table 3 for the original images, IR-MAD, and the relaxation-based image normalization. From the table, it can be observed that the overall assessment shows that our proposed relaxation method achieves the highest correlation coefficient among the three methods (original, IR-MAD, and relaxation). This indicates the effectiveness of our relaxation algorithm in maintaining image similarity across different spectral bands both before and after normalization, contributing to an enhanced accuracy and consistent image representation.

**Table 2.** Accuracy evaluation through MAE and RMSE.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Normalization Method | Accuracy assessment | | | | | | | | | |
| Egypt | | Brazil | | Greece | | USA | | Overall | |
| MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE |
| Original Images | 7.5 | 9.0 | 12.4 | 15.7 | 6.5 | 7.8 | 5.6 | 6.8 | 8.0 | 9.8 |
| IR-MAD | 5.1 | 6.0 | 7.6 | 9.3 | 5.4 | 6.3 | 4.6 | 5.5 | 5.7 | 6.8 |
| Relaxation Algorithm (Proposed) | **1.7** | **2.1** | **6.2** | **7.6** | **4.3** | **5.0** | **3.1** | **3.7** | **3.8** | **4.6** |

**Table 3.** Similarity evaluation through correlation coefficient.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Normalization Method | Similarity assessment | | | | |
| Egypt | Brazil | Greece | USA | Overall |
|  |
| Original Images | 94.50% | 90.06% | 93.05% | 91.12% | 92.18% |  |
| IR-MAD | **97.98%** | 92.24% | 93.95% | 91.25% | 93.85% |  |
| Relaxation Algorithm (Proposed) | 97.64% | **92.45%** | **94.70%** | **91.25%** | **94.01%** |  |

1. **Conclusions**

The results of this study lead to the conclusion that the proposed relaxation algorithm serves as a proficient technique for enhancing image consistency in multitemporal cross-sensor image datasets. Both qualitative and quantitative evaluations demonstrate that our relaxation algorithm surpasses the performance of IR-MAD and the original images by mitigating image disparities, retaining significant features, and enhancing the precision and uniformity of surface reflectance values. The introduced relaxation algorithm holds promise as a valuable resource for researchers and professionals engaged in projects involving such datasets.

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