Selected Topics in Image Processing

Change detection algorithms

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Introduction

Hyperspectral imaging is a powerful technology for detecting subtle changes in images taken at different times. This project focuses on two methods for change detection in hyperspectral imaging: Covariance Equalization (CE) and Chronochrome(CC). The goal is to explore and compare the effectiveness of these methods in detecting changes between hyperspectral images taken a few hours apart.

Chronochrome is an algorithm that requires pixel-level registration to model atmospheric and environmental effects on the spectral signature of each pixel. Covariance Equalization (CE) is introduced as an alternative that does not require image registration. CE estimates signature evolution using only the "before" and "after" statistics of hyperspectral measurements. By analyzing these images using both methods, This project aims to detect and quantify changes more accurately.

Objectives

Analyze Effectiveness: Evaluate the performance of Covariance Equalization & Chronochrome in detecting changes between hyperspectral images.

Identify Improvements: Explore potential enhancements to the method to increase its accuracy and reliability.

Algorithms Derivation

In the derivation of the algorithms for Covariance Equalization (CE) and Chronochrome (CC), the primary objective is to enhance the accuracy of change detection in hyperspectral imaging. Specifically, the CC algorithm aims to minimize the mean squared error (MSE) between the predicted and actual values by using a transformation matrix that leverages temporal correlations between images. This is achieved through the matrix Wiener filter, which provides the minimum MSE solution, making $CX^{-1}x$ the best linear approximation of y. On the other hand, the CE algorithm focuses on equalizing the covariance matrices of the images taken at different times. It achieves this by transforming the covariance of the second image to match that of the first image, thereby normalizing the data and improving the detection of significant changes against natural background variations.

1.**Mean-Cenered data**: let Let {x} and {y} represent two sets of mean-centered hyperspectral signals from the same scene captured at two different times. Each signal is an N-dimensional vector corresponding to one pixel.

2.**Covariance Matrices**: Define the covariance matrices for the two sets as:

$$X \equiv \langle xx^T \rangle, \quad Y \equiv \langle yy^T \rangle$$

and the temporal covariance matrix as:

$$C \equiv \langle yx^T \rangle$$

3.**Linear Estimate**: A linear estimate of y from x is given by:

$$y \approx Lx$$

Where L is the transformation matrix.

4.**Error Matrix**: the associated error matrix E is defined as:

$$E = \langle (y - Lx)(y - Lx)^T \rangle$$

Expanding E and using the assumption that {x} inhabits all available dimensions so X is non–singular, we get:

$$E = \left\langle \{(y - CX^{-1}x) + (CX^{-1} - L)\, x\} \, \{(y - CX^{-1}x) + (CX^{-1} - L$$

When the two factors are multiplied, the cross terms vanish identically, resulting in:

$$E = \left\langle (y - CX^{-1}x)\, (y - CX^{-1}x)^T \right\rangle + (CX^{-1} - L)\, X \, (CX^{-1} - L)^T$$

5.**Minimum Mean Squared Error (MMSE) solution**: he minimum mean squared error (mmse) solution that minimizes the trace of E is:

$$L_{CC} = CX^{-1}$$

This the Chronochrome (CC) transformation or matrix Wiener filter.

6.**Covariance Equalization (CE) Solution**: To derive the CE solution, we expand the error matrix E using the definitions of X, Y, and C:

$$E \approx Y - LXL^T$$

This defines the CE family of transformations. The CE transformation that satisfies this is:

$$L_{CE} = Y^{1/2}X^{-1/2}$$

Both methods leverage the rich spectral information in hyperspectral images but approach the problem of change detection from slightly different perspectives, with CC focusing on temporal correlations and CE on normalizing covariance structures without requiring precise pixel-level registration.

Simulation

The simulation conducted by Roytman and Bodner utilized two hyperspectral images, "self_test_rad" and "blind_test_refl" from the Rochester Institute of Technology (RIT), employing Python and NumPy for implementation. The process included data loading, normalization, covariance matrix calculation, and anomaly detection. Followed by ROC analysis to evaluate detection performance.

Data Source

The dataset used in this simulation consists of hyperspectral images from the Rochester Institute of Technology (RIT). These images provide detailed spectral information with each pixel containing 126 different wavelength bands. The images were captured a few hours apart, allowing for the analysis of changes over time.

Process

1**.data loading**: The hyperspectral images from the RIT dataset were loaded into the Python environment.

2.**Normalization**: The data was normalized to ensure that the mean of each image was zero.

3.**Civariance Matrix Calculation**: Covariance matrices for the images were calculated using NumPy.

4.**Target injection**: A target was injected into each pixel of the second image with a small perturbation to simulate changes in the scene.

5.**Anomaly Detection:** The anomalies were detected using the calculated difference and its covariance matrix.

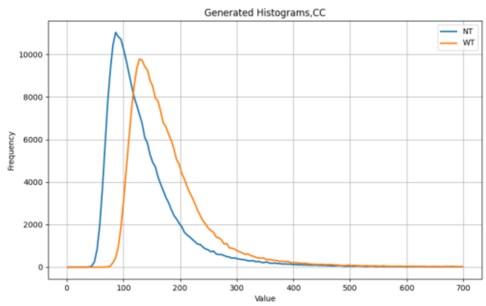
6.**ROC Analysis**: An ROC curve was built based on the histograms of anomaly scores with and without target injection to evaluate the detection performance.

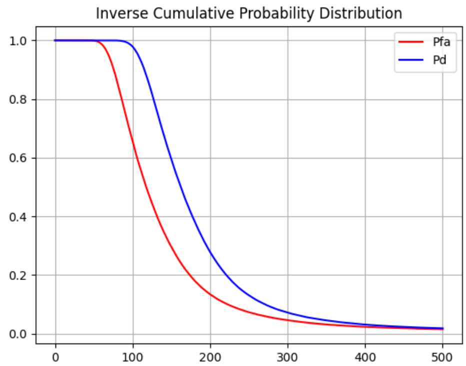
Target Injection and Algorithm Execution

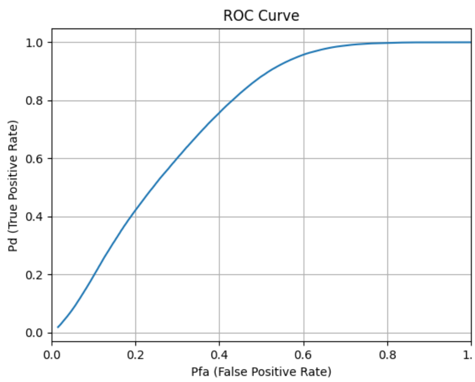
To simulate a change in the scene, we injected a target into each pixel of the second image with a small perturbation. The perturbation P was set to 0.01, and the target t was defined as the pixel value at location (5,5) in the image cube.

The process of injecting a target into each pixel and running the algorithm on the modified image allows us to determine the anomaly values that each pixel would receive if a target were added to it. This approach works because it effectively simulates the presence of a target in every pixel, enabling the algorithm to detect anomalies as if each pixel were individually targeted. This method does not affect the way the algorithm would run if a target were added to each pixel separately, as the perturbation is small and localized, ensuring that the overall statistical properties of the image remain consistent.

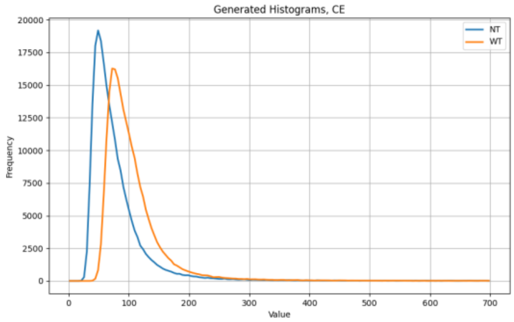
Chronochrome graphs:

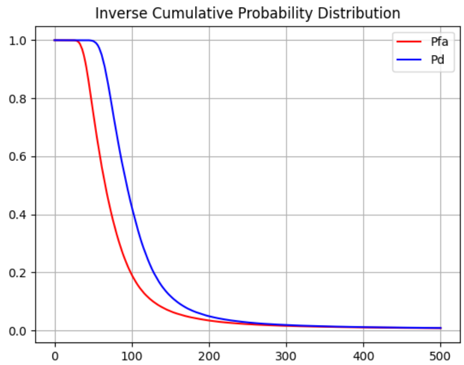


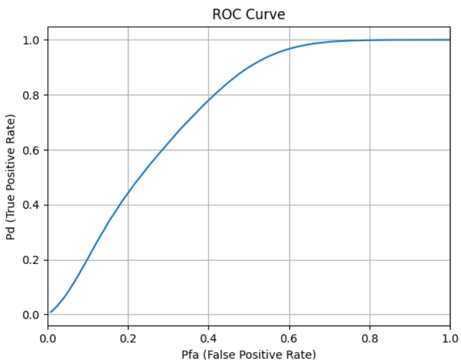




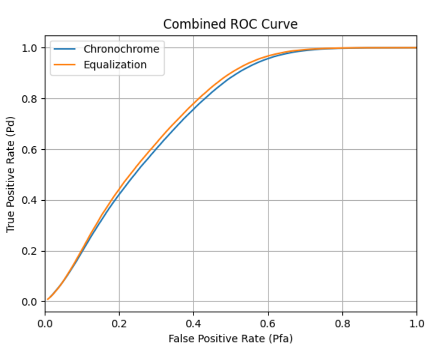
Equalization graphs.







Combined ROC



Results

The ROC curve demonstrates that Covariance Equalization performs slightly better than Chronochrome in detecting anomalies. The area under the curve for Covariance Equalization is marginally higher, indicating its superior sensitivity and accuracy in this particular simulation. This improvement suggests that Covariance Equalization can more effectively leverage the spectral and temporal information to distinguish between true changes and background noise in hyperspectral images.

Expanded Research and Findings

In expanding their research, Roytman and Bodner introduced a new normalization method aimed at enhancing local contrast and improving anomaly detection robustness. This method normalizes each pixel by subtracting the average value of its neighboring pixels. The expanded simulation demonstrated significant improvements in both Chronochrome and Covariance Equalization methods. The study also explored the potential impact of this new normalization method on detecting larger targets.

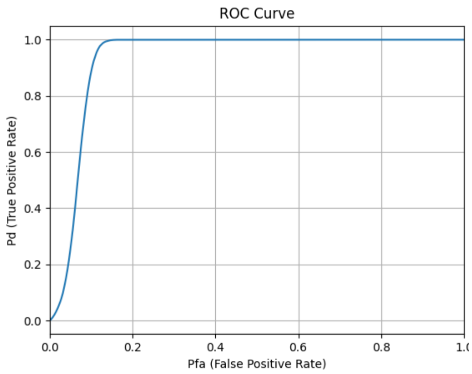
New Normalization method

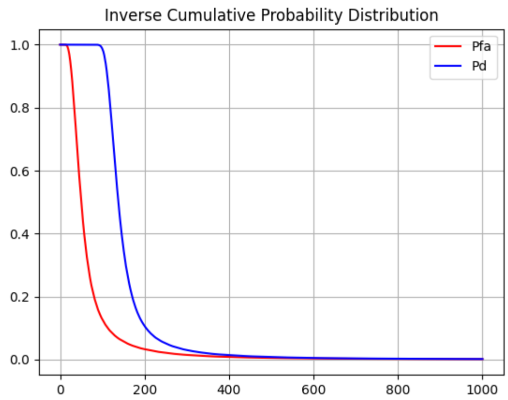
The new normalization method processes each element in the 3D hyperspectral image matrix by subtracting the average of its neighboring elements.

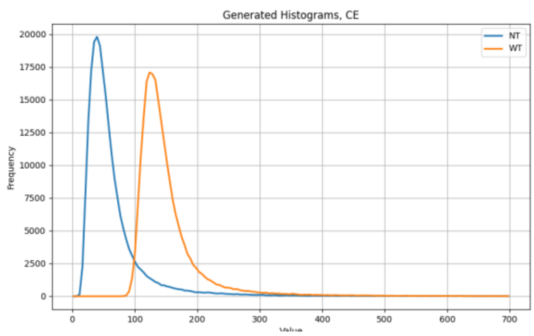
Expanded Simulation Process

In this expanded simulation, the new normalization method was applied to the hyperspectral images before performing anomaly detection using both the Chronochrome and Covariance Equalization algorithms. The same target injection and anomaly detection steps were followed, and an ROC curve was generated to compare the performance of the new normalization method with the previous approach.

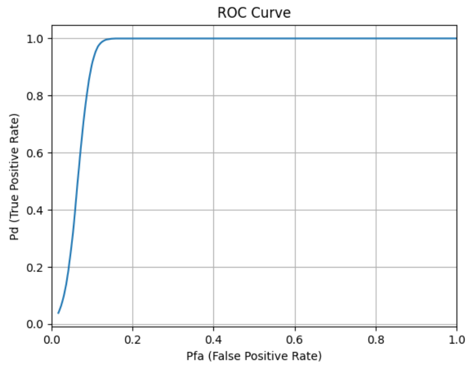
Innovation Equalization graphs

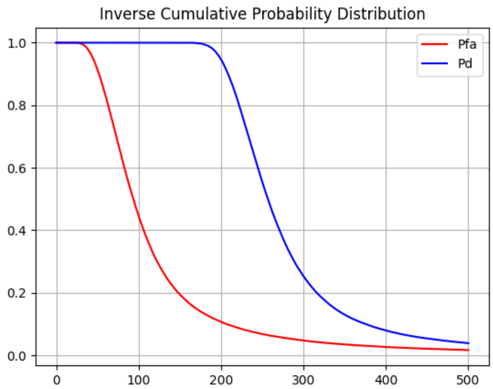


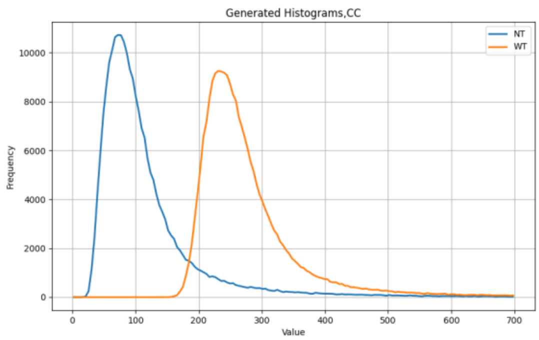




Innovation Chronochrome graphs

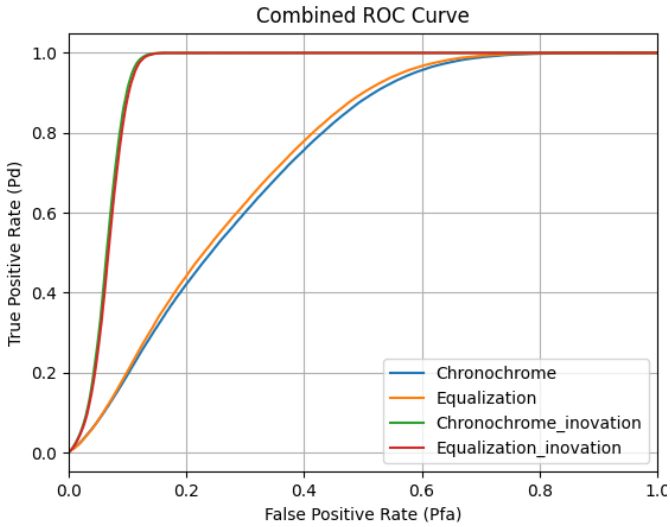






Combined Roc Curve Analysis

The ROC curve compares the performance of the Chronochrome and Covariance Equalization methods before and after this new normalization approach.



Observations

Chronochrome Merthod: The ROC curve for the Chronochrome method shows improvement after applying the new normalization method. The true positive rate (Pd) increases more rapidly with the new normalization, indicating better performance.

Covariance Equalization Method: Similarly, the Covariance Equalization method also shows significant improvement with the new normalization method. The true positive rate is higher for the same false positive rate (Pfa) compared to the previous approach.

Innovation Results: The new normalization approach labeled as "Chronochrome_innovation" and "Equalization_innovation" shows that both methods significantly benefit from the enhanced local contrast normalization. The Chronochrome innovation has the best performance for this simulation.

Potential Impact on Larger Targets

1.**Local Contrast Enhancement**: The new normalization method enhances local contrast by focusing on the differences between each pixel and its neighbors. This can be beneficial for detecting small, subtle changes but might have varying effects on larger, more homogeneous targets.

2.**Edge Detection**: For larger targets, the boundaries (edges) between the target and the background are critical. The new normalization method could potentially enhance these edges, making the target more distinguishable. However, the interior pixels of a large, homogeneous target might be less affected by this method.

3.**Homogeneity of Larger Targets**: If a large target is relatively homogeneous, the new normalization method might not provide a significant advantage, or even compromise the results compare to traditional normalization methods. The pixel values within the target area might be normalized to similar values, reducing the contrast between the target and the background.

Evaluation with Larger Targets

To evaluate the effectiveness of the new normalization method with larger targets, such as a building spanning multiple pixels, the following steps can be taken:

1.**Simulate Larget Target**: Introduce a larger target into the hyperspectral image, spanning multiple pixels, and compare the detection performance using both the new and traditional normalization methods.

2.**Roc Curve Analysis**: Generate ROC curves for both methods, specifically analyzing the detection rates of larger targets.

3.**Visual Inspection**: Conduct a visual inspection of the anomaly maps to see how well the edges and interiors of larger targets are detected with each normalization method.

Conclusion

The updated ROC curve demonstrates that the new normalization method significantly improves the performance of both Chronochrome and Covariance Equalization algorithms. Although the Equalization had a better results the Chrnochome innovation results was slightly better than CE innovation , showing the highest true positive rates and lowest false positive rates. This indicates that CC is slightly more effective in leveraging the detailed spectral and temporal information to detect anomalies in hyperspectral images. By incorporating the new normalization method, the detection performance of both algorithms is enhanced, making them more robust and accurate in identifying changes and anomalies in hyperspectral imaging data.

Reference

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Kwan, C., Ayhan, B., Larkin, J., Kwan, L., Bernabé, S., & Plaza, A. (2019). Performance of Change Detection Algorithms Using Heterogeneous Images and Extended Multi-attribute Profiles (EMAPs). *Remote Sensing*, 11(2377). https://doi.org/10.3390/rs11202377

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