Extraction of GCP chips from GeoCover using Modified Moravec Interest Operator (MMIO) algorithm

Outline for the document

1. Introduction

Many applications in the field of remote sensing require registering two or more images. For example, in change detection analysis, the two images have to be correctly registered in order to perform spatial/spectral change analysis. Sometimes, the registration processes are also involved while creating a precise satellite data product by registering the less precise satellite data with highly precise data like DOQ. The brute force method of comparing and registering every pixel in the two images is computationally prohibitive particularly in the applications of satellite remote sensing data. Instead, only a sample set of points in the image is used for comparison and registration. This sample set of points should have two important characteristics for proper registration.

1. The points should be well defined and easily identifiable in the other image.
2. The points should be well distributed over the entire image.

Some of the approaches found in the literature considered one of the two above characteristics and in several other cases, both the characteristics were considered but these were limited to only computer vision applications and not for applications involving satellite data.

In this current algorithm, a similar approach used by computer vision people for point detection is used with some modifications to make it suitable for satellite remote sensing data. The current approach uses an Interest Operator algorithm coupled with multi-scale approach to determine very good control points in one image that can be used to register with another image. The initial approximation for these points in the other image can be obtained from the satellite model and the grey-scale correlation or Mutual Information correlation algorithm can be used to register the points to sub-pixel accuracy.

This document describes only the methodology to detect the interesting points from the reference image and not the entire registration process.

1.1 Motivation

The original genchips algorithm in IAS (to detect the points in the image to be used for registration) did not take into consideration that the points selected should be well defined and good candidates for correlation. This algorithm uses a simple approach of selecting points at regular intervals (evenly spaced) within the image. It selects the points such that the points are equally spaced along rows and columns. This simple method of selection makes the distribution of points more uniform over the entire image, but selects points that might not correlate for several reasons such as, the points are over water, a homogenous region, or clouds, etc. This particular problem has caused the registration to fail in cases where the scenes have small islands with clouds and oceans. To address this issue, the new algorithm is developed that considers both the distribution and well-defined point criteria in its approach.

1.2 Introduction to GeoCover data

The Landsat GeoCover 2000 dataset is a collection of precision orthorectified Landsat ETM+ scenes with spatial pixel resolutions of 14.25, 28.5, and 57.0 meters for the panchromatic, reflective, and thermal bands, respectively. These data sets are comprised of all nine Landsat ETM+ spectral bands and are in a UTM (Universal Transverse Mercator) map projection with a geodetic accuracy of better than 50 meters RMSE. These GeoCover scenes are used as a base or reference scene to select points and image chips, to be used for registering any ETM+ or TM scenes. This establishes a common geometric reference for image registration while creating precision terrain corrected Landsat products accurate to 50 m RMSE.

1.3 Selection of band to extract GCP chips

The GCP chips are extracted from band 5 of the GeoCover 2000 scenes. A study was conducted to determine the ETM+ multi-spectral bands that are most invariant over time. The study applied principal component analysis (PCA) to time series of three WRS scenes, each containing different land cover types within the scene.

1.3.1 The Principal Component Analysis

Principal component analysis (PCA) involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

The steps to check the suitable band for point selection and chip extraction are given below.

a. Selection of data
b. Creation of data for PCA analysis.
c. Comparison of results to determine the suitable band.

a. Selection of data

The data were selected such that the analysis are performed and tested across different landcover types including forests, agricultural area, lakes/water bodies, high relief areas and cities. The WRS path/row for the three selected scenes are 12/29, 28/29 and 41/36.

b. Creation of data for PCA analysis

The multi-date dataset for each target area includes six scenes acquired at different seasons between 2001 and 2002 (SLC_On scenes). All the scenes were processed to L1Gs product using the Landsat 7 Image Assessment System (IAS). The same band layer from all the scenes (same target area) were extracted and registered together manually to create a new scene with multiple temporal layers of the same band. For ex: The band 1 layer from the scene acquired on six dates (01/31/02, 03/17/01, 05/23/02, 07/26/02, 09/25/01 and 12/01/02) for Path/Row 41/36 were extracted and these 6 layers were registered together to form a Band 1 scene for 41/36. Similarly, all the other multi-spectral bands of Landsat 7 (excluding Band 6) were extracted and 6 layered band images for the particular target area is created. Thus, a total of 6 "band images" (b1,b2,b3,b4,b5,b7) were created for each target region. These band images are only a function of time as they were all formed by same multi-spectral band of Landsat 7 over the same region.

c. PCA analysis and Results

The first principal component is taken to be along the direction with the maximum variance. The eigenvalues of the first principal component are the highest among all the components. If a particular band is highly invariant across time, then all the layers within that band image will be highly correlated, and the band image information will be concentrated in the first principal component. As a result, the eigenvalue for the first principal component will be large compared to the eigenvalues for the other principal components (eigenvalue percentage). The eigenvalue percentage for the most temporally invariant band image will be highest in comparison with the other band images.

Principal component analysis was performed for each of the band images for the three test sites and the corresponding eigenvalue percentages were compared. For the 41/36 and 28/29 target regions, band 5 showed highest invariance with respect to time whereas for the scene 12/29, band 4 was the highest. However, the band 4 and band 5 eigenvalue percentages differed only slightly for this site. Hence, the band 5 image is considered highly invariant with time, over a range of scene content, and is used for extracting the GCP chips.

1.4 Approach

The new approach uses the interest operator algorithm to identify the well-defined points. The Moravec Interest Operator algorithm is performed over an image to determine the interesting points using a specified window size suitable for satellite data.
The original image is upsampled by a factor of 2, and downsampled by a factor of 1.5. A cloud mask is created using a simple cloud detection algorithm, so that the interest operator is performed only outside the masked regions, in areas identified as cloud-free. The Moravec Operator algorithm is performed on both resampled images and on the original image. Unwanted points are removed by comparing their computed interest operator values to a threshold value.

The interest operator results from all three images (original and resampled) are sorted and compared. Only those points/pixels identified in all three lists are retained. The other points are removed from the list. A constraint check is performed on the remaining points in the list (original resolution list) to ensure that the distance between any two points is greater than a threshold distance. The simple distribution logic of segmenting the image into zones and picking a minimum number of points from each zone ensures that the algorithm produces well-distributed points over the entire scene.

1.5 Other Related Work

1.5.1 Genchips

The previous 'genchips algorithm' is a simple algorithm of dividing the number of samples and lines of the image by a fixed number. The input parameter to this algorithm is the required number of points along the line direction and sample direction.
A = Image_size_row / Num_points_row
B = Image_size_column / Num_points_col

Select the points such that they are 'B' distance away along the sample direction and 'A' distance away along the line direction. This will result in a set of well-distributed points over the entire image.

Disadvantages:

1. Points selected may not be well defined / identifiable in the other image.
2. Chances of mis registration / failure to register when the scene contains water or clouds.

1.5.2 Feature Matching

Feature based matching determines the correspondence between two image features. Most feature based techniques match extracted point features (this is called feature point matching), as opposed to other features, such as lines or complex objects. The feature points are also commonly referred to as interest points. Poor contrast areas can be avoided with feature based matching.

In order to implement feature based matching, the image features must initially be extracted. After the features are extracted, the attributes of the features are compared between two images. The feature pair having the attributes with the best fit is recognized as a match.

Disadvantages:

1. The image registration tool in IAS uses grey scale matching as opposed to feature attributes. Hence this method is not easy to implement with the existing algorithms in IAS.

1.6 Introduction to Interest Operators

Local-feature-based approaches have proven successful in many vision problems including scene reconstruction, image indexing, object recognition and registration. The basic idea is to focus attention on a comparatively sparse set of especially salient image points, also called interest points, that are located using an interest operator.

Many different interest point detectors have been proposed with a wide range of definitions for what points in an image are interesting. Some detectors find points of high local symmetry, others find areas of highly varying texture, while others locate corner points. Corner points are interesting as they are formed from two or more edges and edges usually define the boundary between two different objects or parts of the same object. Many corner detectors / interest operators have been developed and some of the most popular operators are Moravec operator, Forstner operator, Wang & Brady operator, SUSAN operator. Due to their computational complexity, most of these algorithms are not well suited to large scale satellite remote sensing data processing applications.

1.6.1 Moravec Interest Operator

The Moravec Operator is a corner detector since it defines interest points as points where there is a large intensity variation in every direction. Directional variance is measured over small square windows. Sums of squares of differences of pixels adjacent in each of four directions (horizontal, vertical and two diagonals) over each window are calculated, and the window's interest measure is the minimum of these four sums. Features are chosen where the interest measure has local maxima. The feature is conceptually the point at the center of the window with this locally maximal value.

1.6.2 Forstner Interest Operator

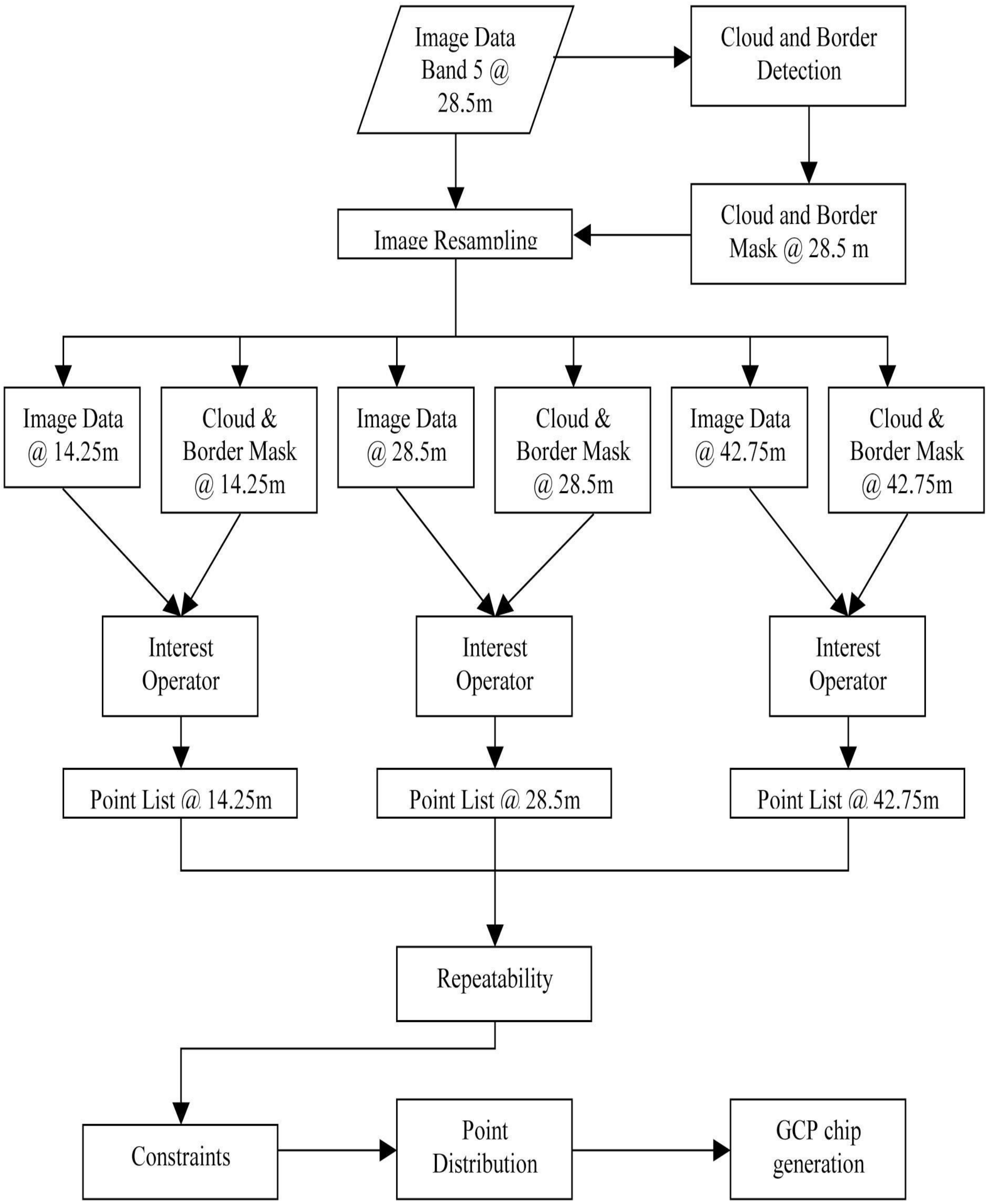
The Forstner interest operator is the first step for Forstner's feature-based image matching algorithm. The Forstner interest operator selects points such that they fulfill requirements like distinctiveness, invariance, stability, seldomness and interpretability. This interest operator first selects optimal windows based on the covariance matrix and then selects an optimal point within each window and then a measure for seldomness is applied to the selected points to satisfy the requirements for point selection. Since the operator is coupled with the image matching technique, it uses the two scenes together to select the points and uses the information derived in this process for matching the two images. This algorithm is very popular among the computer vision groups, but it is computationally extensive to be applied for satellite remote sensing data.

2. Methodology

The need for a new approach from the existing "genchips" approach is mainly to satisfy the three basic requirements for the selection of points.

1. No points over water or clouds
2. Well distributed points
3. Well defined points

The Moravec interest operator is modified to satisfy the above three conditions and also to make it work well with satellite remote sensing data. The Moravec interest operator is selected for this approach due to its simplicity and its effective results for the current work. The methodology involved to create the interesting points using the interest operator is outlined below in the form of a flow chart.



Flowchart of MMIO algorithm

The algorithm follows a series of steps that can be summarized under following titles. Each of these steps is described below.

1. Cloud and Border detection
2. Image Resampling
3. Interest Operator
4. Repeatability
5. Constraints
6. Point distribution logic
7. GCP chip extraction

2.1 Cloud and Border detection

Cloud detection

The presence of clouds and shadows in the remote sensing data has always caused problems for different applications by obscuring the actual ground information. The different types of clouds and its different characteristics also made the detection of clouds very difficult. There are several algorithms to detect clouds, however, the MMIO (Modified Moravec Interest Operator) algorithm uses a simple approach for cloud detection. A simple, somewhat conservative approach to cloud detection is justified since the algorithm is designed to be applied to the GeoCover 2000 data set, which is nominally cloud free. For this application it is sufficient to simply avoid image regions that are, or may be, clouds. It is necessary for the MMIO algorithm to detect clouds, as one of the requirements is that the algorithm should not include clouds in the extracted control points. A cloud mask is created so that the algorithm avoids all cloud pixels and also some proximal region around the detected clouds.

The cloud detection algorithm used in this approach is based on ratio of two bands. The two bands that show predominant cloud characteristics (ETM+ bands) are Band 6 and Band 3. Band 6L (low gain version of band 6), which is a thermal band, usually has very low (cold) values for clouds whereas Band 3 often saturates for the clouds. Hence those pixels whose ratio is beyond the threshold will be marked as cloud pixels. The ratio is checked for each pixel in the image and a cloud mask is generated based on its value with ‘0’ for clouds and ‘1’ for non-cloud pixels.

Since the resolution of GeoCover band 6L is 57m whereas for band 3 it is 28.5m, the band 6L image is resampled to 28.5m before determining the ratio of the two bands.

The cloud detection logic is expressed as

$$P(i,j) = 0 \quad \text{if} \quad P(i,j)_{b3} = 255 \text{ or } P(i,j)_{b3} >= \text{threshold}*P(i,j)_{b6}$$
$$P(i,j) = 1 \quad \text{otherwise}$$

Where

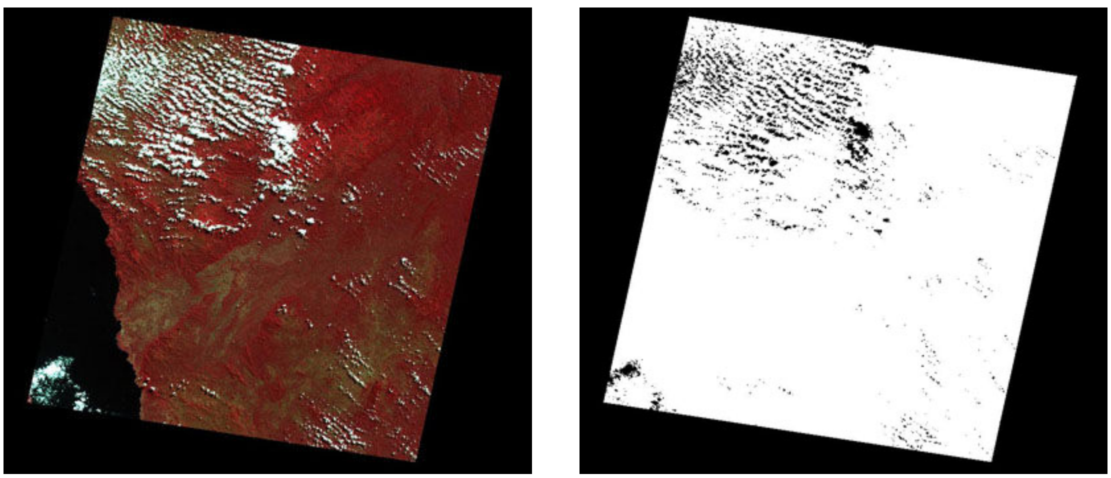
$P(i,j)$ is the pixel value for the cloud mask at line i and sample j

$P(i,j)_{b3}$ is the pixel value for the band 3 at line i and sample j

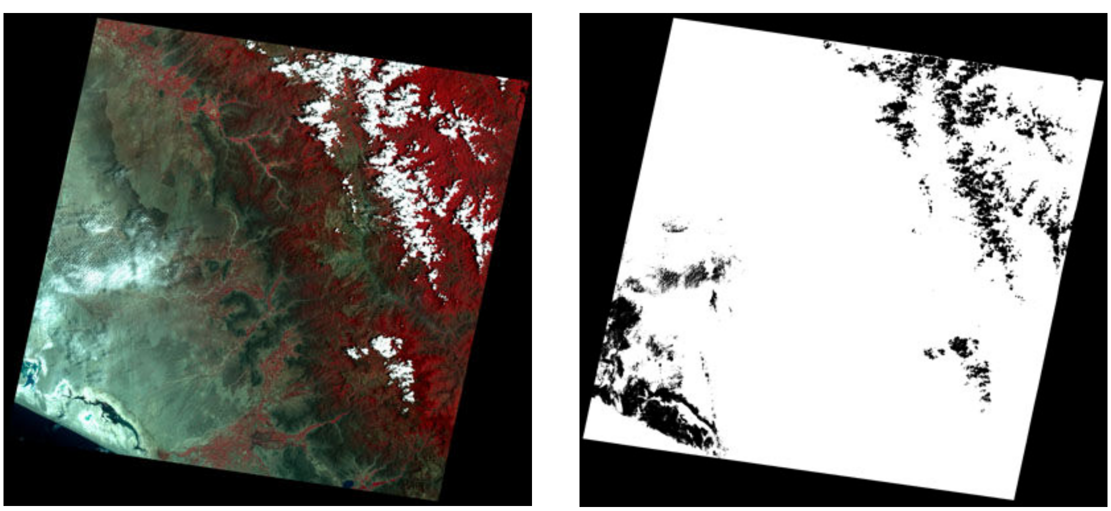
$P(i,j)_{b6}$ is the pixel value for the resampled band 6 at line i and sample j

The threshold was determined based on trial and error method. Several GeoCover scenes were tested with different threshold values and based on the test, the threshold is set at 2 when band 3 was operated in high gain. The dynamic range for band 3 low gain is 1.5 times that of high gain. Hence the threshold for low gain was determined to be 1.5 times lower than that of the high gain threshold. Thus, the high gain threshold was set at 2 and low gain threshold at 1.33. The ETM+ records in two thermal bands, one for low gain and another for high gain. For the MMIO cloud detection logic, always the low gain thermal band (6L) is used.

The figures below shows some of the test results with the cloud detection logic.



WRS P/R : 168/67, Band combination : 4,3,2, Band 3 gain state : High, Thr = 2



WRS P/R : 10/64, Band combination : 4,3,2, Band 3 gain state : Low, Thr = 1.33

As this cloud detection logic is very simple and is prone to mis-classification, a buffer radius of 40 pixels around each cloud pixel is also classified as cloud pixels. This increases the probability that the GCP chip of 64x64 pixels is devoid of cloud pixels. The figures above did not include the buffer of 40 pixels.

Border detection

The GeoCover band images are projected in the north up UTM projection system. Hence the actual image data will be seen rotated with respect to the image file extent. These extra pixels (also called fill region) are assigned the value ‘0’ to differentiate the fill region from the image region when the product is created. The border mask is simply a mask that has value ‘0’ for fill regions and value ‘1’ for image regions.

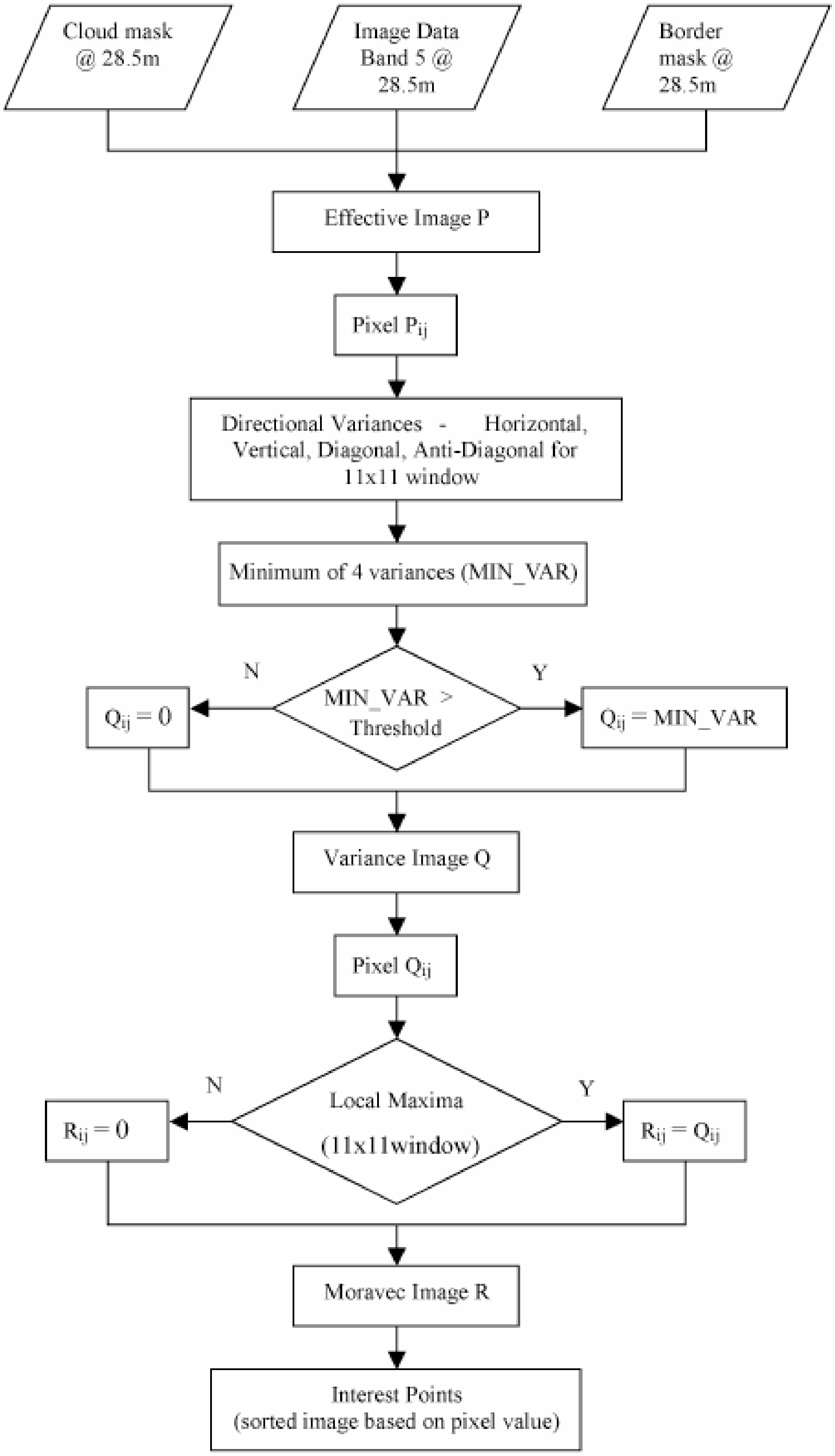
Image multiplication operation is performed between the cloud mask and border mask to create a new mask that shows the valid pixels to run the Moravec interest operator. This greatly reduces the time to run the interest operator algorithm and at the same time satisfies one of the requirements for the selection of points (cloud avoidance).

2.2 Image Resampling

The MMIO algorithm requires an image-resampling algorithm to resample images to different resolutions. Two different resampling algorithms are used, one for resampling the image data and another for resampling the image mask data. The resolution for the GeoCover Band 5 image data is 28.5m. This image is upsampled by a factor of 2 to get the same scene at 14.25m resolution using cubic convolution resampling algorithm. The original image is also downsampled by a factor of 1.5 to get the image at 42.75m resolution using cubic convolution resampling algorithm. The cloud mask and the border mask at the original resolution of 28.5 m are also resampled to get masks at 2 other resolutions (14.25m and 42.75m) using nearest neighbor resampling algorithm.
These resampled and the original images form the ‘input data’ to the Moravec Interest operator algorithm.

2.3 Moravec Interest Operator

The Moravec Interest Operator is a corner detector and it defines interest points as points where there is a large intensity variation in every direction. The original algorithm is slightly modified to suit to the needs for the current approach. The Modified Moravec Interest Operator algorithm can be summarized in the form of a flowchart as shown below.



Flowchart for Moravec Interest Operator algorithm

As the flowchart shows, the input for this operator is the actual image data and the two masks (one for clouds and other for the border). By multiplying the two masks, we can get another mask that shows the active pixel for which the Moravec operator has to be performed. The Moravec operator starts with each active pixel (from mask) and then determines the directional variances for this pixel in the horizontal, vertical, diagonal, anti-diagonal directions for a window size of 11x11. (The entire 11x11 window is not required to be cloud-pixel free.) Considering the time, resolution of the data, and better results with the interest operator, the window size for the variance calculation was determined to be best at 11x11. The directional variance in the horizontal direction is computed by the following formula,

$$Q_{H}(i,j) = \sum_{k=i-5}^{k=i+5} \left(g(k,j) - g(i,j) \right)^{2}$$

where g(i,j) is the pixel value for the active pixel in the line i and sample j of the input image.

Similarly, directional variance along the vertical direction, diagonal direction and anti-diagonal directions are also determined for the active pixel P_{ij}. The interest measure of the pixel is calculated based on whether the minimum of the four variances is above or below the threshold. The interest measure of a pixel is ‘0’ if the minimum variance is below the threshold and it is equal to the minimum variance otherwise. Interest measure is determined in the same way for all the active pixels and a floating-point type variance image is created. The interest points are selected where the interest measure has local maxima within a window size of 11x11. These interest points are then sorted based on their interest measure in the descending order to get the best point at the top of the list. The threshold value for the Moravec Interest Operator is set at 10,000 to remove the homogenous regions like clouds, water or even less contrasting homogenous landmass that would fail to correlate. This threshold value is applicable only for the case of the 11x11 window size. For a 11x11 window, there are 10 values that are squared and summed while determining any directional variance. Hence by setting the threshold at 10,000 the average DN^2 of each value is about 1000. This implies that the average difference between a pixel in the window to the center of the window is about 30 DN. Several tests were conducted to check the validity of the threshold for the low contrast features like water bodies, desert, dry lands, etc in the GeoCover scenes. The test results showed that the threshold value is quite effective in removing the spike in homogenous regions and as well not using any homogenous regions for point selection.

2.4 Repeatability

The Moravec Interest Operator algorithm as described above can produce many points that may or may not be well defined due to the inherent problems with the algorithm. The MMIO algorithm uses the ‘repeatability function’ as a means to reduce such false identification of points. In general, if the ground targets are well defined at a specific resolution, they should be identifiable across different resolutions in the image until

either the resolution is too low to make the entire target as sub-pixel or the resolution is too high that the targets are no longer considered well-defined.
Thus the definition of ‘interest point’ for MMIO is not limited to determining the points where the intensity changes in all directions, but also to detect such points at lower and higher resolutions. This definition ensures that detected interest points are well defined based on ground characteristics and not purely based on image characteristics.

The resampled images with their masks are run through the Moravec Interest Operator algorithm (similar to original image @28.5m) and the two point lists are generated one for higher resolution (14.25m) and another for lower resolution (42.75m).

Those points that are found in all three point lists are considered as interest points and all the other points are discarded. The final point list consists of the common points with their coordinates based on the original resolution (28.5m) and sorted (descending) based on interest measure (operator value) at the original resolution.

In the repeatability function, since the images are resampled, a tolerance of 2 pixels is allowed to match the same point across two other resolutions.

2.5 Constraints

The MMIO algorithm uses a constraint to make sure that no two GCP image chips shall contain the same image pixels. This reduces the risk of mis-registration when the interest points are very similar within a small distance.
The constraint equation is given below.

$$\text{if } \operatorname{dist}(P_i - P_j) < 64 \text{ , remove } P_j \text{ if } j > i \quad (i, j = 1 \text{ to } n)$$

where,
P refers to the point (interest point) on the point list (after repeatability)
i, j are the index (after sort) for the interest points in point list (after repeatability)
n, refers to the number of points in the final point list

Thus, between any two points that are closer to each other by less than 64 pixels, the point that has lower interest measure are removed, while the other point is retained.

The point list after the constraint check consists of interest points that are not closer to each other by less than 64 pixels and sorted based on their interest measure (original resolution).

2.6 Point distribution logic

One of the requirements for the MMIO is that the points are well distributed over the entire image. The distribution of the points is important, as the images will be registered using these points. The solution obtained from the registration process will be used to

correct the satellite model while creating a precision corrected product. So if the distribution of points is not over the entire image but concentrated over a small region of the image, it might result in a poor fit.
The distribution logic in the MMIO algorithm maintains a balance between the distribution of points and well-defined interest points.
The distribution logic can be explained in steps as

1. Extract 'n' number of points from the top of the point list. (high interest measure). These points will form the first 'n' number of points in the final point list for MMIO algorithm. If there are less than 'n' number of points in the point list, then all the points are selected for the final point list.
2. Divide the image into rectangular segments or zones.
3. Within each zone, a maximum of 'k' points can be included in the final point list. If 'm' number of points in a particular zone is already selected in step 1 (m<=n), then (k-m) number of additional points are selected from that particular zone such that the selected points have the highest interest measure among the remaining points within that zone. If (k-m) < 0 then no additional points are selected in this zone. This ensures that no more than 'k' points will be selected in this step and the points are not duplicated in the final list. If the maximum number of points available within a particular zone is less than 'k', then all the available points within that zone is selected (excluding points selected in step 1 from this zone) and if the zone contains no points, then no points will be selected from that zone.
4. The selected points in steps 1- 3 will be sorted based on their interest measure and forms the final point list from the MMIO algorithm.
5. If the total number of points are less than a threshold value (40) then the 'genchips' algorithm (default parameter of 20x20) will be run to increase the number of points as this increases the probability that a scene can be registered correctly. This is done only when the MMIO fails to generate enough points (ex: desert and homogenous regions throughout the scene). The 'genchips' determined point list is added with the interest operator point list.

Thus for a normal scene with mostly land, the points are well distributed over the entire image, whereas in cases with small islands, the well defined points within the islands alone will be selected, as the zone without any points (removed by threshold in Moravec interest operator algorithm) will not add any points in to the final list. Even for the case where there are not enough features, the coupling of genchips algorithm with MMIO algorithm can produce more points with better results.

2.7 GCP chip extraction

Once all the well defined points for an image are identified by their line and sample coordinates in the image, the next important step is to determine the location of these points with respect to the ground coordinate system and create an image chip of specific size. The image chip size required for IAS is 64x64 pixels. So an image extent of 64x64 pixels is extracted from the GeoCover Band 5 image with the interest point at the center of the chip. Since the GeoCover image is precision terrain corrected product in the UTM projection system, the UTM coordinates for the given line and sample can be calculated from the file header information. In order to get the elevation of the point, the NED dataset is used to get the elevation information for places within CONUS and GTOPO30 for regions elsewhere. UTM coordinates of the points are converted to the DEM projection coordinate system to derive the elevation information for the corresponding points.

The GCPLib file stores the ground coordinate information (UTM coordinates and elevation) for all the image chips for a particular scene. These chips are used to register any other scene (same geographical extent) for creating a precision corrected product.

3. Results

The MMIO algorithm has worked well in several test cases and some of the results are discussed here. The algorithm was tested under several different scenarios, which includes,

1. Cloud free scenes (predominantly land)
2. Cloud free scenes with land and water bodies
3. Cloud free island scenes (small / chain of islands)
4. Cloud covered scenes (predominantly land)
5. Cloud covered scenes with land and water bodies
6. Cloud covered island scenes (small / chain of islands)
7. Desert scenes.

For testing the MMIO algorithm, the cropped image from the original GeoCover 2000 scene was used instead of the full image for certain cases.

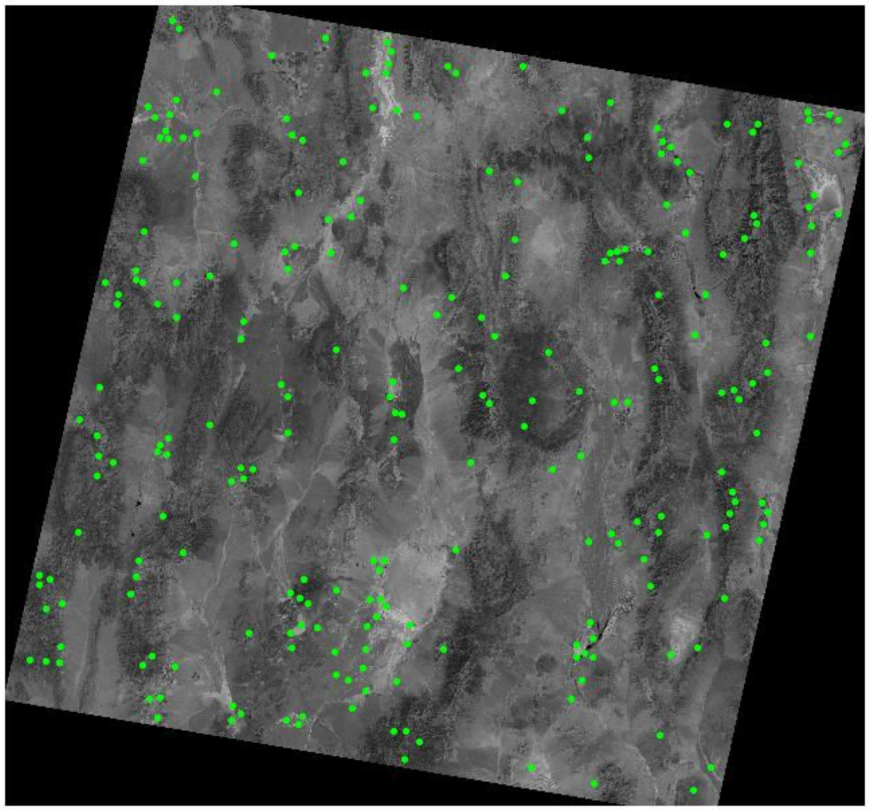
Test Case 1: Cloud free scenes with land

The figure below shows the selection and distribution of the points for the first test case. The green dots in the image show the interest points selected by the MMIO algorithm. These points, as can be seen, are well distributed over the entire image.

Evaluation

The accuracy of the MMIO algorithm was evaluated by registering a SLC-Off (ETM+) scene with GeoCover-derived control sets created using both the current ‘genchips’ algorithm and the ‘MMIO’ algorithm. For this evaluation, the SLC-Off scene with the lowest ACCA score (for cloud cover) was used. In this test case, both the algorithms produced GCP chips that correlated correctly and produced a well registered precision corrected product.

GeoCover 2000 (ETM+) - Band 5
WRS Path/Row: 40/33, Cloud free scene (land)



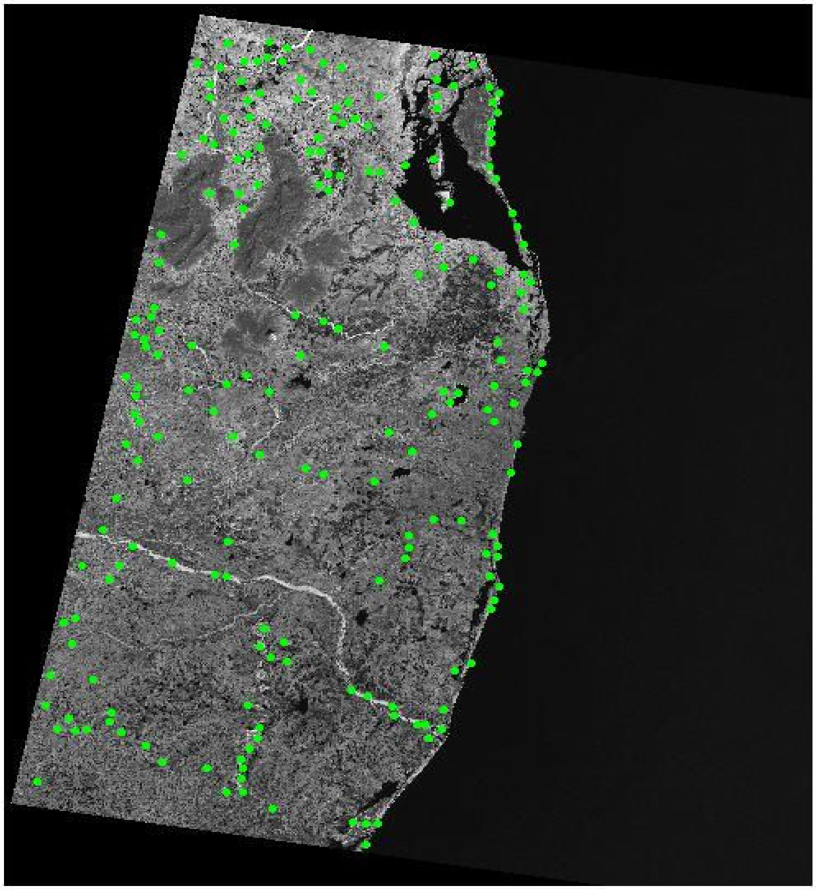
Test Case 2: Cloud free scenes with land and water bodies

The green dots in the figure below show the selection of interest points using MMIO algorithm. The dark region on the right half side of the image is an ocean / water bodies. It is very evident from the figure that the MMIO algorithm completely avoided the water bodies for interest point selection.

Evaluation

The accuracy of the MMIO algorithm was evaluated by registering a SLC-Off (ETM+) scene with GeoCover-derived control sets created using both the current 'genchips' algorithm and the 'MMIO' algorithm. For this evaluation, the SLC-Off scene with the lowest ACCA score (for cloud cover) was used. Both the algorithms produced GCP chips that correlated correctly and produced a well registered precision corrected product. However the product correlated with fewer points using existing genchips in comparison to the MMIO based GCP chips.

GeoCover 2000 (ETM+) – Band 5
WRS Path/Row: 142/51, Cloud free scene (land and water bodies)



Test case 3 : Cloud free island scenes (small / chain of islands)

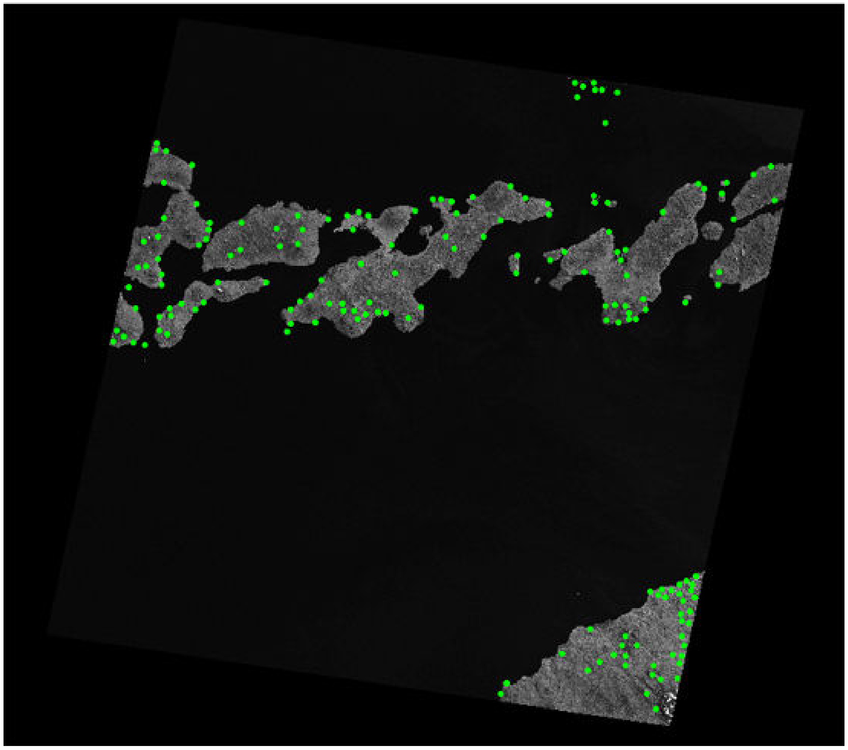
There have been many incidences in which the scenes fail to register correctly using the existing genchips algorithm particularly over island scenes. In order to test and evaluate the MMIO algorithm, tests were conducted for both cloudy and cloud-free island scenes. The figure below shows the cloud-free island scene with the interest points selected using MMIO algorithm in green dots. It is once again clear that the MMIO algorithm avoided selecting points over water bodies. Though most of the water regions were avoided, some points were selected (top right corner of the image) that had very thin clouds over the ocean. These clouds were not detected by the MMIO cloud logic and hence were identified as interest points. These are false identifications with the MMIO algorithm.

Evaluation

The accuracy of the MMIO algorithm was evaluated by registering a SLC-Off (ETM+) scene with GeoCover-derived control sets created using 'MMIO' algorithm. For this evaluation, the SLC-Off scene with the lowest ACCA score (for cloud cover) was used.

Most of the selected interest points correlated correctly and produced a well registered precision product. As expected, the falsely identified interest points (over clouds) did not correlate and hence were thrown out as outliers and were not included in precision solution.

GeoCover 2000 (ETM+) – Band 5
WRS Path/Row: 110/66, Cloud free island scene



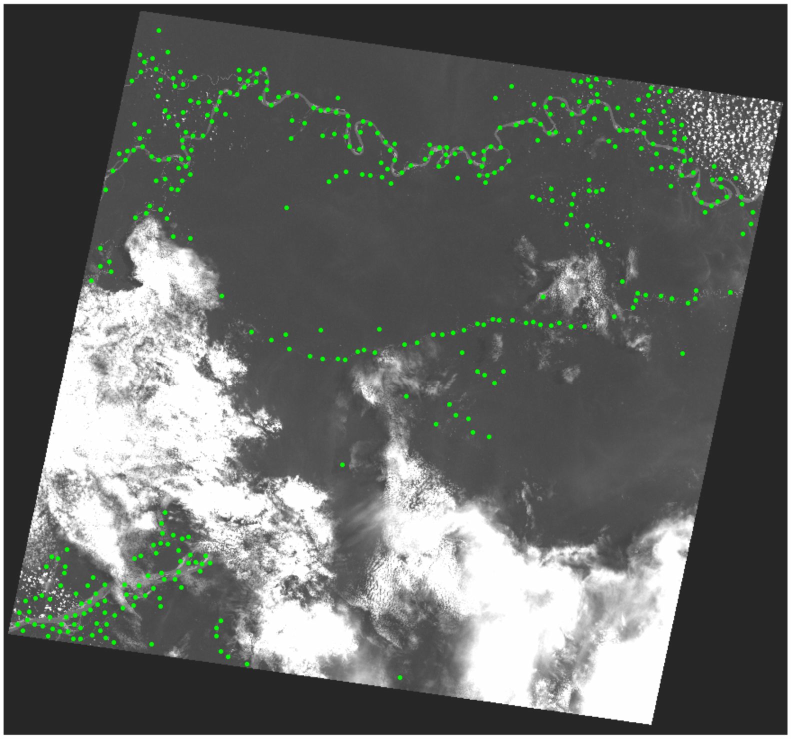
Test case 4 : Cloud covered scenes (land)

This is one of the important test cases because about 70% of the satellite data are obscured by clouds either partially or completely. Also there are regions where the satellite data at any time of the year will always have clouds. Some studies require precision corrected satellite data for these regions for certain applications. Hence it is required that the MMIO algorithm is capable of selecting and identifying more number of cloud free GCP chips from the reference scene as the scene being correlated may also be cloudy over some of the selected GCP chips. In the figure below, the green dots represents the interest points selected by the MMIO algorithm.

Evaluation

The accuracy of the MMIO algorithm was evaluated by registering a SLC-Off (ETM+) scene with GeoCover-derived control sets created using both the current ‘genchips’ algorithm and the ‘MMIO’ algorithm. For this evaluation, the SLC-Off scene with the lowest ACCA score (for cloud cover) was used. Both the algorithms produced GCP chips that correlated correctly and produced a well registered precision corrected product. The MMIO algorithm had more points that correlated and were used in precision than the existing genchips algorithm.

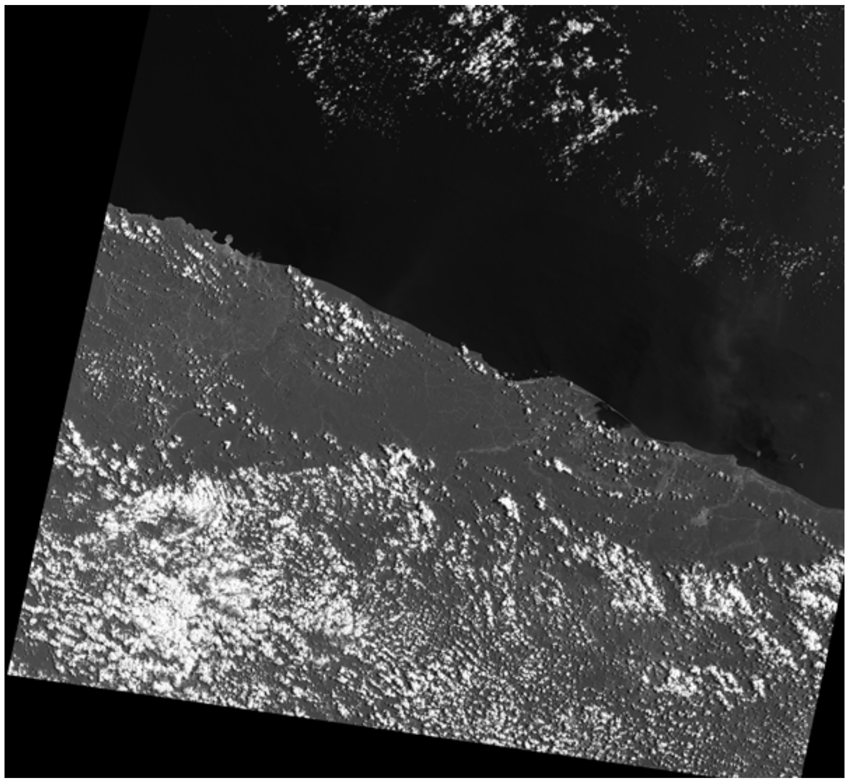
GeoCover 2000 (ETM+) – Band 5
WRS Path/Row: 5/62, Cloud covered scene (land)



Test case 5 : Cloud covered scenes (land and water bodies)

This is one of the important test cases as the existing genchips algorithm often fails for this particular case. Due to the presence of popcorn type clouds over land, there are chances that the existing ‘genchips’ derived GCP chips might have clouds and hence would fail correlation. In this example, both the GeoCover scene and the SLC_Off scene had clouds. The figure below show the cropped GeoCover scene used for GCP chip extraction.

GeoCover 2000 (ETM+) – Band 5
WRS Path/Row: 100 / 62, Cloud covered scenes (land and water bodies)



Evaluation

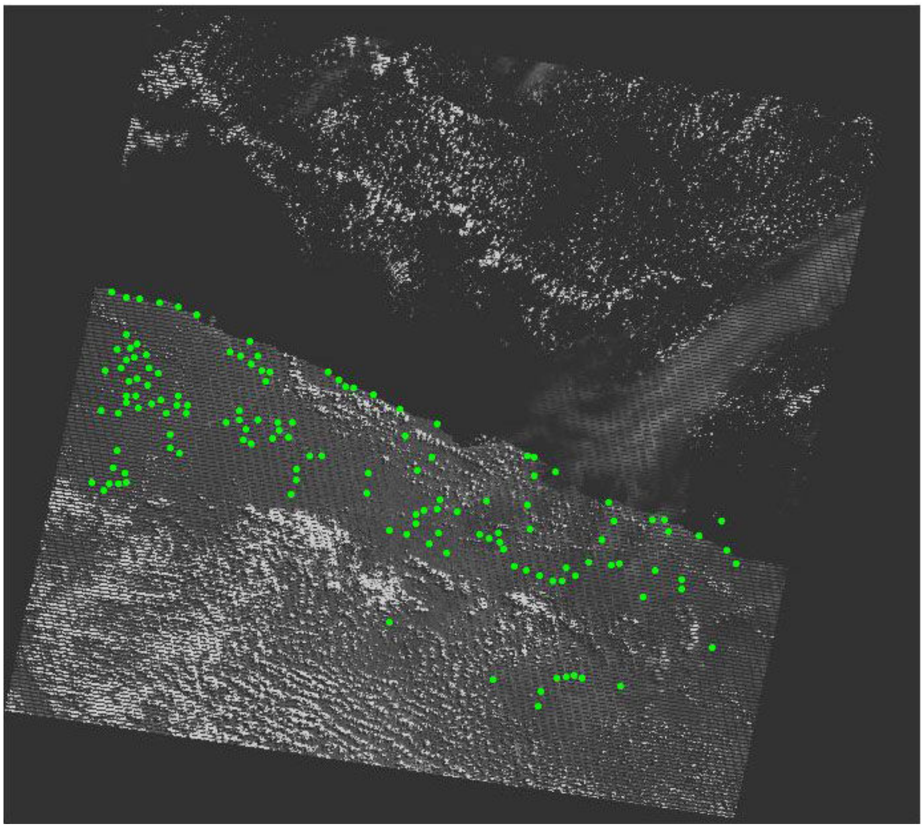
The evaluation of this test case, like other cases, was conducted to compare the MMIO algorithm with the existing genchips algorithm. The SLC-Off scene is used for the comparison.

The control point spacing parameter for the 'genchips' algorithm is set at 20x20 (20 points along row and 20 points along column to form 400 points over the entire scene including fill regions). The number of points generated within the image region is 237. These 237 GCP chips were used to register the SLC-Off scene with the GeoCover. The registration results showed that only 28 points were successfully registered.

The MMIO algorithm generated 491 points (within the image) for the same GeoCover scene. The registration results showed that 138 points registered successfully with a highly reliable solution.

The figure below shows the location of the successfully correlated and registered points based on MMIO (green dots) overlaid on the SLC-Off scene.

ETM+ (SLC-Off)
WRS Path/Row: 100 / 62, Cloud covered scenes (land and water bodies)



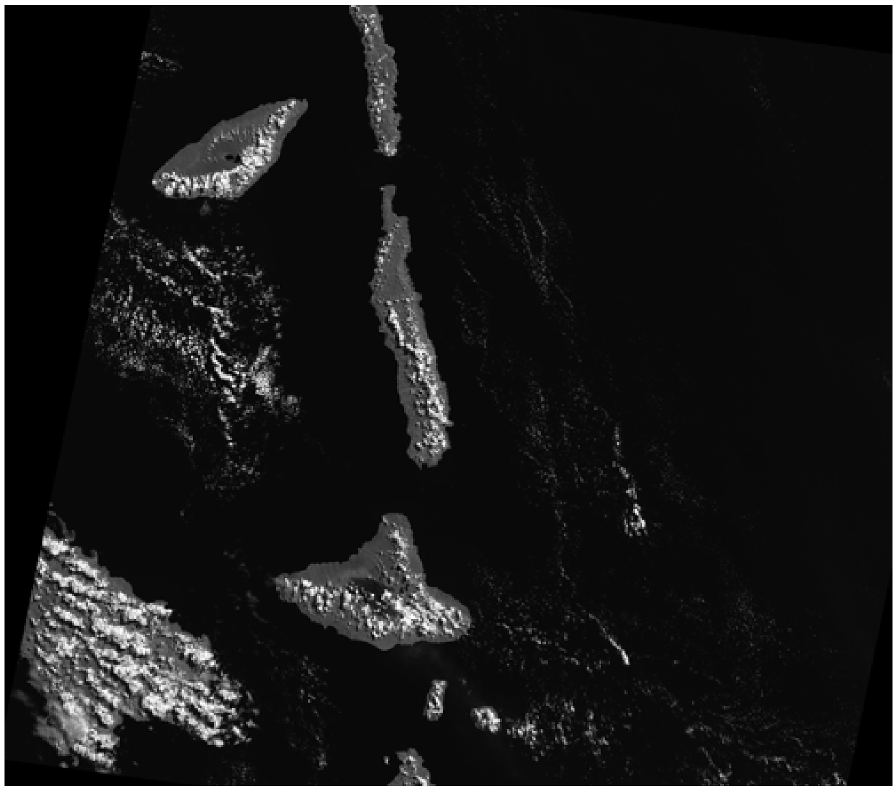
When the parameter for the 'genchips' algorithm was changed to 30x30 it produced about 709 points within the image. However, only 80 points registered successfully to produce a reliable solution.

Though the 'genchips' algorithm was able to produce a reliable solution by successfully registering the two images in this test case, it still registered only a small number of points compared to the MMIO algorithm. This shows that the probability of registering GCP chips derived from MMIO algorithm is higher than that of the current 'genchips' algorithm.

Test case 6 : Cloud covered island scenes (small / chain of islands)

This test case like the one above is another important test case to demonstrate the capability of the MMIO algorithm. The test case procedure is similar to the one above. The figure below show the cropped GeoCover scene used for GCP chip extraction.

GeoCover 2000 (ETM+) – Band 5
WRS Path/Row: 81 / 71, Cloud covered island scenes



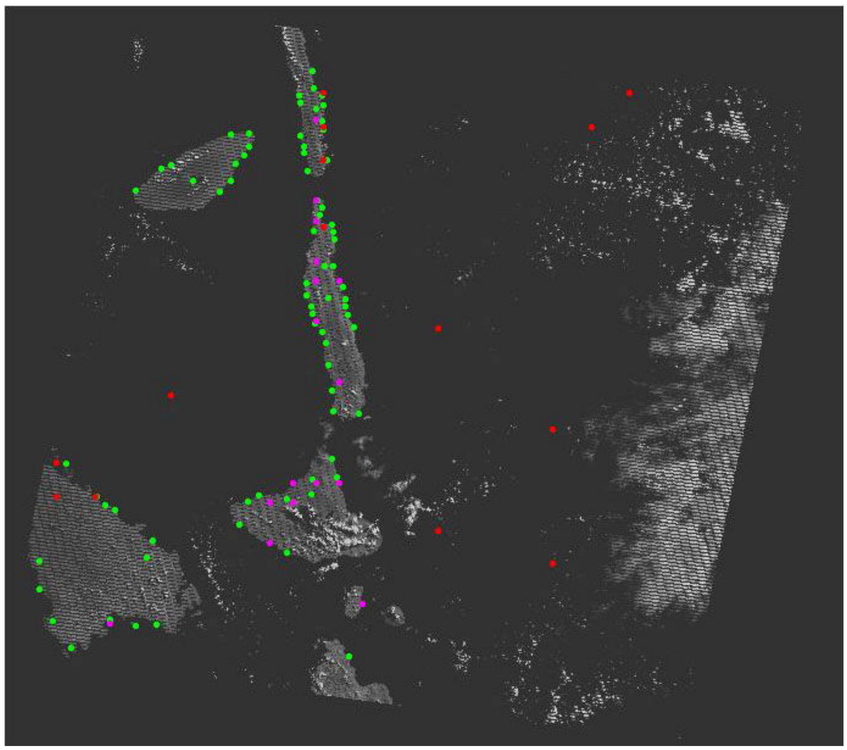
Evaluation

The test case was conducted similar to the previous test case with the ‘genchips’ control point spacing parameter set to 20x20. This produced 241 points (inside image) of which 14 points correlated but the resulting registration solution was highly unreliable and incorrect. The solution did not produce valid results and hence the registration failed in this case. The MMIO algorithm produced 473 points of which 74 points registered successfully with a valid and reliable solution.

When the parameter for the ‘genchips’ algorithm was changed to 30x30 it produced more than 724 points within the image. In this case, 15 points registered successfully to produce a reliable and valid solution.

The figure below shows the location of the successfully correlated points based on MMIO (green dots), genchips (20x20 - red dots), genchips (30x30 - pink dots) overlaid on the SLC-Off scene.

ETM+ (SLC_Off)
WRS Path/Row: 81 / 71, Cloud covered island scenes

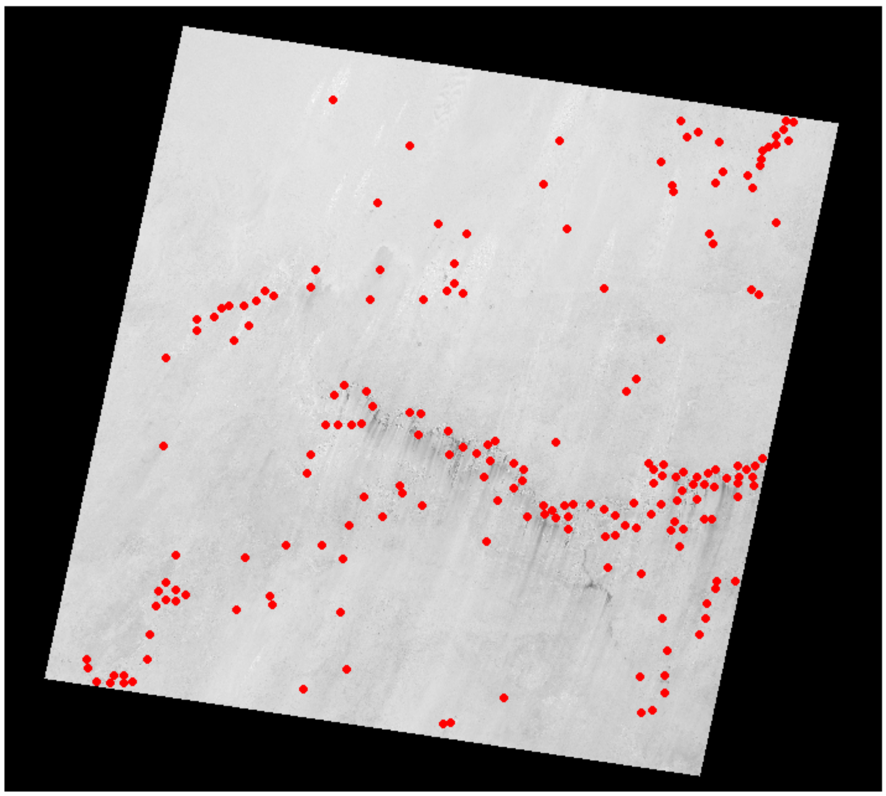


The 'genchips' algorithm failed to register correctly and hence did not produce a valid solution. By increasing the points, though the registration was successful, it resulted only in 15 points. This shows that the MMIO algorithm not only has a higher probability to register points but also produces more points that can register consistently and correctly. The drastic reduction in the number of points that finally correlated in the MMIO algorithm (from 473 points to 80 points) were mainly due to the clouds on the SLC-Off scene that were found over the GCP chip locations.

Test case 7 : Desert scenes

The desert scenes are usually homogenous regions and hence it is important to test and evaluate the MMIO algorithm in selecting the interest points for these cases. The chances of correlation of points over desert are always less due to the spectral nature of the regions. However, some of the desert scenes have certain features or sand dunes which do not change over a period of time. The figure below show the interest points determined by the MMIO algorithm (red dots) overlaid on the GeoCover scene.

GeoCover 2000 (ETM+) – Band 5
WRS Path/Row: 177 / 46, Desert scene



Evaluation

The accuracy of the MMIO algorithm was evaluated by registering a SLC-Off (ETM+) scene with GeoCover-derived control sets created using 'MMIO' algorithm. Most of the selected interest points correlated correctly and produced a well registered precision product. This scene had some features that enabled the MMIO algorithm to select them as interest points. However, there may be some desert scenes which may exhibit no features at all. This is discussed in the limitation of MMIO algorithms.

Other Test cases

The MMIO algorithm was tested with other scenes with clouds in the GeoCover reference (Path/Row: 116 / 52, 104/64, 102 / 62) and has successfully registered and produced valid solutions for all these scenes. But for one particular desert scene, the MMIO algorithm produced a much smaller number of points. The scene was completely covered with desert and had no features to select as well-defined points. However, as described in the methodology, when the MMIO did not find enough points, it will select points using the original genchips algorithm and add them to the GCP chip library along with the interest points selected using the MMIO algorithm. This is also a limitation with the current MMIO algorithm.

4. Limitations

The MMIO algorithm has some disadvantages that restrict the performance of MMIO algorithm on some specific cases. Three limitations that have been observed in the testing of the algorithm are discussed here.

1. Cloud interference
2. Desert scenes or scenes with no features
3. Processing time to run the algorithm

Cloud Interference

The different type of clouds and their different characteristics makes cloud detection very difficult. There are several algorithms to detect clouds, however, the MMIO algorithm uses a simple approach for cloud detection by performing a ratio of two bands.
This simple approach can cause mis-identification of cloud pixels and as a result there might be both commission and omission errors in cloud detection. The commission errors (due to the identification of bright spots or snow pixels in the image as cloud pixels) are not bad as they are not a good source for controls. However, the omission errors might have serious impact with the final results. When an actual cloud pixel (not identified by simple cloud detection algorithm) is closer to the water bodies, (water bodies - low DN and cloud - high DN), then the MMIO algorithm identifies those cloud pixels as interest points with higher interest measure due to increased differences in DN between the adjacent pixels (Test case 3 as an example). This would cause the correlation to fail with these interest points.
Though this is one of the limitations, the buffer radius of 40 pixels surrounding each detected cloud pixel avoids the problem in most of the cases. Thus for cloudy scenes, the selection of interest points is dependent on the correct identification and detection of clouds in the image.

As an alternative, if some complex accurate cloud detection algorithm is used, then the results with MMIO algorithm will be better, but this might increase the processing time depending on the complexity of the cloud detection algorithm.

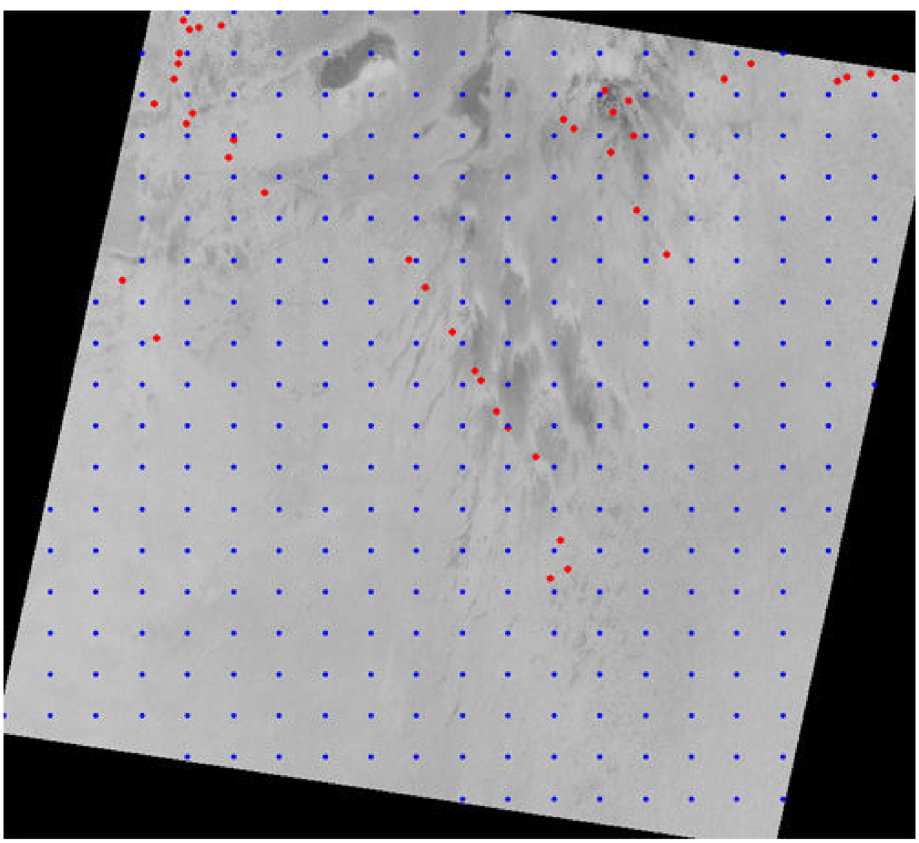
Desert scenes or scenes with no features

In general, the desert scenes (featureless scenes) are considered as problematic scenes for image registration. In one of the tests with desert scenes, the MMIO algorithm produced many fewer points. The desert scene did not have identifiable features that the MMIO algorithm can select as interest points. The intensity variation within a window (11x11 pixels) was so low that these points failed to pass the threshold for the Moravec Interest Operator algorithm.

This is considered as one of the limitations with MMIO, but in general, by reducing the threshold the number of points can be increased but at the cost of selecting featureless points. The probability of such featureless points to correlate is also low and hence to increase the points, the 'genchips' algorithm was used and these points are added to the smaller list of MMIO generated points for GCP chip generation.

The figure below show the interest points generated based on MMIO (red dots) and the 'genchips' based points (blue dots) overlaid on the GeoCover scene. The GeoCover scene in this figure is slightly stretched in order to show contrast in the image.

GeoCover 2000 (ETM+) – Band 5
WRS Path/Row: 162 / 44, Desert scenes



Processing Time to run the algorithm

The processing time required to create GCP chips using MMIO algorithm is significantly higher compared to that of the 'genchips' algorithm. Since the genchips algorithm is simple, it takes less than a minute whereas the MMIO algorithm on an average would take approximately 20 minutes to create GCP chips using the same system configuration as for 'genchips' algorithm. The reason for such a big difference in processing time is due to the computational complexity of the MMIO algorithm in comparison with the genchips algorithm.

The MMIO algorithm is run only once per WRS path/row to produce GCP chips from the reference image (GeoCover 2000 - band 5) unless the reference scene for registration is changed or updated.

Prototype Code

Language: C
System Configuration: Intel(R) Xeon(TM) CPU 2.80GHz : 2 CPUs Total
Vendor: Dell Computer Corporation
Product Name: PowerEdge 2650
Total Memory: 3857224 kB
Processing time per WRS scene: 20 minutes.(appx)

5. References

Hans P. Moravec, Towards Automatic Visual Obstacle Avoidance. In Proc. of 5th International Joint Conference on Artificial Intelligence, 1977.

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