Abstract- Image co-registration is one of critical steps required for Digital Elevation Model (DEM) generation. The traditional Image co-registration algorithms are divided into two main categories, Area Based Matching (ABM) Methods and Feature Based Matching (FBM) Methods, each of these categories has its own advantages and drawbacks. In this paper, a new algorithm for image co-registration step based on the combination between ABM and FBM is proposed, where, Minimum Eigenvalue algorithm is used as FBM and compared to Harris corner detector algorithm. The performance of the proposed algorithm is evaluated by coherence factor. Results show that the propose algorithm is more efficient than using only Harris corner detector algorithm or Minimum Eigenvalue algorithm.

Keywords- FBM, ABM, Minimum Eigenvalue, Coherence factor, co-registration.

I. INTRODUCTION

Synthetic Aperture Radar (SAR) is a type of radar used in geodesy and remote sensing where it can potentially measure centimeter scale changes in deformation over time spans of days to years. Elevation data is a fundamental layer for any Geographic Information System (GIS). Digital Elevation Model (DEM) is a 3-D presentation of the surface. The main steps for DEM generation are image co-registration [1,2,3], interferogram flattening [4], interferogram filtering [5], phase unwrapping [6,7] and geocoding [4].

An image registration system can be considered as a black box that receives a reference image and a sensed image then it resamples the sensed image to spatially align with the reference image. Image registration is defined as a method to find the offset or misalignment between two or more images for a certain place. Automated Image registration requires sequential and iterative execution of different phases for generating registered data products with high quality.

There are two main approaches for co-registration, area based method and feature based matching method. The typical Area Based method procedure consists of coarse co-registration and fine co-registration. Coarse co-registration, is the process to find the offset between the two SAR images in range of pixels and shift the slave image according to this shift to align the master image . Fine co-registration is the process to find Sub-pixel offset between the two SAR images. Approximately the cross-correlation between the master and slave images is used [1,2]. For Feature Based method, there are many algorithms used to select accurate numbers of Control Points (CPs) in the reference image and in the slave image. Feature Based algorithms include Harris Corner Detector [1,3], Scale Invariant Feature Transformation (SIFT) [1,2], ... etc. In this work, a co-registration algorithm is proposed to find the misalignment between the miss registered images. The algorithm is based on the combination between the Feature Based methods and the Area Based methods. The cross-correlation function is used to find the offset between the images in the range of pixels and the minimum eigenvalue is used to find the sub pixel shift between the images. The paper is designed as the following: In section two, the methodology is explained. Section three, experiments and results are shown. Finally, conclusion is clarified in section four.

II. METHODOLOGY AND ALGORITHM

While, Coarse co-registration process match two SAR images at up to one or two pixels’ accuracy including searching for coarse image offsets and shifting the slave image [1,2,3], Fine co-registration process find the Sub-pixel tie points on the two images for sub-pixel accuracy including searching for sub-pixel tie points and fitting transformation equations onto these tie points then, resampling one of these two SAR images based on the transformation equations. Co-registration performance is usually evaluated by coherence Image [1,2,3,8,9,10]. Figure 1 shows a proposed work flow for SAR image co-registration.

2.1 Coarse Co-registration

Coarse co-registration is the step where two SAR images are co-registered at up to one or two pixels accuracy. Cross correlation is the most commonly used approach for checking the accuracy of Coarse Co-registration. The slave SAR image will be shifted by the offset value in both range and azimuth directions [1,2,3].

2.2 Fine Co-registration

It must be noted that the cross correlation is not only
for coarse co-registration, but also a common criterion for fine co-registration. Fine co-registration will be investigated using Minimum Eigenvalue Algorithm. After coarse co-registration, very small offsets in the azimuth direction can be detected, where a number of researchers had applied only the four parameter transformation equations onto sub-pixel tie points. Most offsets are only proportional to the range pixel location [1,2,8,9,10,11,12].

Corner Detection finds corners in an image using minimum eigenvalue method was introduced in [11]. The block finds the corners in the image based on the pixels that have the largest corner metric values. The Shi-Tomasi corner detector is based entirely on the Harris corner detector [11,12]. However one slight variation in selection criteria made this detector much better than the original. It works quite well where the Harris corner detector fails. The Harris corner detector has corner selection criteria. A score is calculated for each pixel, and if the score is above a certain value, the pixel is marked as a corner. The score is calculated using two eigenvalues. That is, you gave the two eigenvalues to a function. The function manipulates them, and gave back a score. Shi and Tomasi suggested that the function should be done away with. Only the eigenvalues should be used to check if the pixel was a corner or not. The score for Harris corner detector was calculated like this (R is the score) in [8].For Shi-Tomasi, it’s calculated as discussed in [11].

\[ \begin{align*}
\text{H} = & \begin{pmatrix} I_x & I_y \\ I_y & I_z \end{pmatrix} \\
\lambda_1 & = \text{max} \left( \begin{pmatrix} I_x & I_y \\ I_y & I_z \end{pmatrix} \right) \\
\lambda_2 & = \text{min} \left( \begin{pmatrix} I_x & I_y \\ I_y & I_z \end{pmatrix} \right)
\end{align*} \]

A corner (in general an interest point) is characterized by a large variation in all directions. By analyzing the eigenvalues, this characterization can be expressed such that if \( \lambda_1 \approx 0 \) and \( \lambda_2 \approx 0 \) then this pixel \((x, y)\) has no features of interest. If \( \lambda_1 \approx 0 \) and \( \lambda_2 \) has some large positive value, then an edge is found. If \( \lambda_1 \) and \( \lambda_2 \) have large positive values, then a corner is found [11,12]. Shi–Tomasi corner detector directly computes the minimum of both \( \lambda_1 \) and \( \lambda_2 \) because under certain assumptions, the corners are more stable for tracking. Note that this method is also sometimes known as Kanade-Tomasi corner detector [11].

Random Sample Consensus (RANSAC) in general is an algorithm for robust fitting of models in the presence of many data outliers. RANSAC loop has 5 main steps, select feature pairs (at random), computing homography (exact), computing inliers, recording the largest set of inliers so far, and finally re-computing least-squares homography estimation on the largest set of the inliers. For RANSAC algorithm, it is important to know how many times we need to run RANSAC (k times) according to number of samples (n samples) for which Smaller is better. The time we need to run RANSAC is calculated as

\[ K = (\log(1-P)/\log(1-p^2)) \]

where \( n \) is number of samples drawn each iteration, \( p \) is probability of real inliers, and \( P \) is probability of at least 1 success after k trials. P is given by

\[ P = (1-(1-p)^k) \]

where \( n \) samples are all inliers, \( (1- p^2) \) is a failure, and \( (1- p^2)^k \) is a failure after K trials [1,2,3,13].

For the proposed algorithm, Minimum Eigenvalue algorithm directly calculates the eigenvalues of the normal cross-correlation matrix. Use of the Coefficients for separable smoothing filter parameter to define a vector of filter coefficients. The block multiplies this vector of coefficients by its transpose to create a matrix of filter coefficients. The block calculates the smaller eigenvalue of the normal cross-correlation matrix corresponds to the corner metric matrix.

2.3 Co-registration Evaluation

The coherence factor between two SAR images is used to evaluate the accuracy of the co-registration process, given two SAR images with corresponding complex pixels \( P_1 \) and \( P_2 \) where \( P_1 = R_1 + jI_1 \) and \( P_2 = R_2 + jI_2 \). Coherence factor \( \gamma \) is a complex number, so \( |\gamma| \) is usually used. The value of \( |\gamma| \) is always between 0 and 1. In this paper, the average of the whole coherence image is used as criteria to evaluate the co-registration results using the proposed algorithm [1,2,14-18].

III. EXPERIMENTAL RESULTS

To evaluate the proposed algorithm, two pairs of SAR images are used. The first pair is a simulated images and the Second pair is , real data, covers Las Vegas in the USA.

A. Results of Simulated images

Average coherence before registration is 0.5476 and
value of pixel shift in range is 0 and in azimuth is 1. After using the proposed algorithm, results were as follows:

- In case of maximum corner points = 2000 and maximum threshold = 0.000001 (TABLE I):
  a) Harris Corner detector algorithm could not achieve any results although using coarse co-registration or not.
  b) Minimum Eigenvalue algorithm:
     i- Without coarse co-registration, average coherence after registration process is 0.8842 and the value of pixel shift is (0,0) in both range and azimuth. Transformation matrix elements are shown:

     \[
     \text{Transformation Matrix} = \begin{bmatrix}
     1.0000 & 0.0000 & 0 \\
     -0.0000 & 1.0000 & 0 \\
     1.0003 & 0.0004 & 1.0000
     \end{bmatrix}
     \]

     ii- With coarse co-registration, average coherence after registration process is 0.8842 and the value of pixel shift is (0,0) in both range and azimuth. Transformation matrix elements are shown:

     \[
     \text{Transformation Matrix} = \begin{bmatrix}
     1.0000 & 0.0000 & 0 \\
     0.0000 & 1.0000 & 0 \\
     0.0002 & 0.0003 & 1.0000
     \end{bmatrix}
     \]

- In case of, maximum corner points = 800 and maximum threshold = 0.000001 (TABLE I)
  a) Harris Corner detector algorithm could not achieve any results even using coarse co-registration or not.
  b) Minimum Eigenvalue algorithm:
     i- Without coarse co-registration, average coherence after registration process is 0.8842 and the value of pixel shift is (0,0) in both range and azimuth. Transformation matrix elements are shown:

     \[
     \text{Transformation Matrix} = \begin{bmatrix}
     1.0000 & 0.0000 & 0 \\
     0.0000 & 1.0000 & 0 \\
     0.0000 & 0.0000 & 1.0000
     \end{bmatrix}
     \]

     ii- With coarse co-registration, average coherence after registration process is 0.8842 and the value of pixel shift is (0,0) in both range and azimuth. Transformation matrix elements as shown:

     \[
     \text{Transformation Matrix} = \begin{bmatrix}
     1.0000 & 0.0000 & 0 \\
     0.0000 & 1.0000 & 0 \\
     0.0000 & 0.0000 & 1.0000
     \end{bmatrix}
     \]

Table I, Simulated SAR images

<table>
<thead>
<tr>
<th>Image Size</th>
<th>1502x1148</th>
<th>Threshold</th>
<th>0.0001</th>
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</thead>
<tbody>
<tr>
<td>Minimum Eigenvalue Algorithm</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corner Points</td>
<td>2000</td>
<td>800</td>
<td></td>
</tr>
<tr>
<td>With ABM</td>
<td>Without ABM</td>
<td>With ABM</td>
<td>Without ABM</td>
</tr>
<tr>
<td>Avg. Coherence before</td>
<td>0.5474</td>
<td>0.5474</td>
<td></td>
</tr>
<tr>
<td>Xcorr. Peak before</td>
<td>0.7435</td>
<td>0.7435</td>
<td></td>
</tr>
<tr>
<td>Xcorr. Peak after Coarse</td>
<td>0.6570</td>
<td>0.6570</td>
<td></td>
</tr>
<tr>
<td>Avg. Coherence after Reg</td>
<td>0.8842</td>
<td>0.8842</td>
<td></td>
</tr>
<tr>
<td>Xcorr. Peak before</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Xcorr. Peak after Reg</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
</tr>
</tbody>
</table>

B. Results of Las Vegas images

Average coherence before registration is 0.5474 and the value of pixel shift in range direction is 199 in range and 6 in azimuth. After using the proposed algorithm, results were as follows:

- In case of, maximum corner points = 2000 and maximum threshold = 0.0001 (TABLE II):
  a) Harris Corner detector algorithm:

     i- Without coarse co-registration, average coherence after registration process is 0.6570 and the value of pixel shift is (0,0) in both range and azimuth. Transformation matrix elements as shown:

     \[
     \text{Transformation Matrix} = \begin{bmatrix}
     1.0000 & 0.0000 & 0 \\
     0.0000 & 1.0000 & 0 \\
     5.9995 & 198.9995 & 1.0000
     \end{bmatrix}
     \]
ii- With coarse co-registration, average coherence after registration process is 0.7444 and the value of pixel shift is (0,0) in both range and azimuth. Transformation matrix elements as shown:

\[
\text{Transformation Matrix} = \begin{bmatrix}
1.0000 & 0.0000 & 0 \\
0.0000 & 1.0000 & 0 \\
-0.0004 & -0.0002 & 1.0000
\end{bmatrix}
\]

b) Minimum Eigenvalue algorithm:

i- Without coarse co-registration, average coherence after registration process is 0.6571 and the value of pixel shift is (0,0) in both range and azimuth. Transformation matrix elements as shown:

\[
\text{Transformation Matrix} = \begin{bmatrix}
1.0000 & -0.0000 & 0 \\
0.0000 & 1.0000 & 0 \\
5.9961 & 198.9989 & 1.0000
\end{bmatrix}
\]

ii- With coarse co-registration, average coherence after registration process is 0.7442 and the value of pixel shift is (0,0) in both range and azimuth. Transformation matrix elements as shown:

\[
\text{Transformation Matrix} = \begin{bmatrix}
1.0000 & -0.0000 & 0 \\
0.0000 & 1.0000 & 0 \\
-0.0039 & -0.0008 & 1.0000
\end{bmatrix}
\]

Table II, Las Vegas, USA SAR image

<table>
<thead>
<tr>
<th>Image Size = 900x2500, Threshold= 0.0001</th>
<th>Corner Points = 2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harris Corner</td>
<td>Minimum Eigenvalue</td>
</tr>
<tr>
<td>With ABM</td>
<td>Without ABM</td>
</tr>
<tr>
<td>Avg Coh before</td>
<td>0.5474</td>
</tr>
<tr>
<td>Xcorr. Peak before</td>
<td>199.6</td>
</tr>
<tr>
<td>Avg Coh. after Coarse</td>
<td>0.6302</td>
</tr>
<tr>
<td>Xcorr. Peak after Coarse</td>
<td>0.0</td>
</tr>
<tr>
<td>Avg Coh. after Reg.</td>
<td>0.7444</td>
</tr>
<tr>
<td>Xcorr. Peak after Reg.</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Table III, Las Vegas, USA SAR image

<table>
<thead>
<tr>
<th>Image Size = 900x2500, Threshold= 0.0001</th>
<th>Corner Points = 800</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harris Corner</td>
<td>Minimum Eigenvalue</td>
</tr>
<tr>
<td>With ABM</td>
<td>Without ABM</td>
</tr>
<tr>
<td>Avg Coh. before</td>
<td>0.5474</td>
</tr>
<tr>
<td>Xcorr. Peak before</td>
<td>199.6</td>
</tr>
<tr>
<td>Avg Coh. after Coarse</td>
<td>0.6302</td>
</tr>
<tr>
<td>Xcorr. Peak after Coarse</td>
<td>0.0</td>
</tr>
<tr>
<td>Avg Coh. after Reg.</td>
<td>0.7445</td>
</tr>
<tr>
<td>Xcorr. Peak after Reg.</td>
<td>0.0</td>
</tr>
</tbody>
</table>

CONCLUSION

This work employs automatic Minimum Eigenvalues algorithm for SAR image co-registration and compared to Harris Corner detector. A quantitative measure for the quality of co-registration based on using Concept of Coherence Image is introduced. Comparison between the use of automatic Minimum Eigenvalues algorithm for SAR image registration and Harris Corner detector yielded to:

a) Every SAR image has its unique co-registration algorithm for high performance, Figure 2.

b) Higher Coherence area indicates a better co-registered location, Figure 3.

c) As Offset between SAR images decreases, Coherence Value increases, Table III.

d) Proposed algorithm “Combination between Area Based matching (ABM) method and Minimum Eigenvalue as feature Based Matching (FBM) method” is better than using Minimum Eigenvalues as Feature Based Matching (FBM) method directly.

e) Proposed algorithm “Combination between Area Based matching (ABM) method and Minimum Eigenvalues as feature Based Matching (FBM)
method” is better than using Harris Corner detector as Feature Based Matching (FBM) method directly with less computational time, Table III.

Finally, this work indicates that the proposed algorithm may lead to good results with areas of same features as that of Las Vegas.

REFERENCES

[16] Leica Geosystems, ERDAS IMAGINE Tour Guides, ERDAS LLC, 2013.