Smoothing of the Surface Estimates from Radarclinometry

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Abstract - ***Radar shape-from-shading (RSFS) technique (Radarclinometry) deals with the recovery of "surface normal", and consequently the surface height through a gradual variation of shading depicted in a radar image. The major objection to RSFS is the ambiguity from uncertain backscatter properties. Involving some constraints such as brightness and smoothness can remove or reduce this ambiguity. Thus, this paper aims to remove the ambiguity of uncertain backscatter properties from RSFS technique. The removal of the ambiguity was carried out by applying smoothness constraint. The effect of the constraint was examined on RADARSAT-1 Standard-7 mode (S7). The accuracy of final absolute heights was evaluated quantitatively by calculating RMSE and R^2 as well as qualitatively. The final accuracy of the absolute heights was found to be improved after 100 iterations.***

Key words: *SFS, 3D Heights, SAR Imageries, smoothness.*

1. INTRODUCTION

3D height has been an important component in most geospatial, environmental, engineering and military related researches and applications. The traditional methods used for generation of 3D heights have resided on ground surveys, existing contour maps, aerial photographs and images, and satellite imageries.

1.1 Conventional Shape from Shading

Shape from shading (SFS) is the process of computing the three-dimensional shape of a surface from an image of that surface (Pargios et al. [12]). The effects of shading or brightness variations on an image are caused by the different orientations of parts of a surface.

The use of a single image cannot always ensure the uniqueness of the shape of an object. Therefore, there will be relatively little effect devoted to exploiting the exact 3D shape reconstruction from the shading information of one image. This problem is resolved by introducing ancillary information to the SFS process.

The basic assumption underlying SFS is a uniform surface reflectivity (Lambert). Several studies investigating Lambertian reflectance model have been carried out on SFS (Kimmel and Bruckstein[9], Wilson and Hancoc[17], and Prados and Faugeras[13]).

From a computational viewpoint, SFS involves solving the image irradiance equation to recover a set of surface normals or surface slopes (Worthington [15]). Horn [5] was the first researcher, who had formulated SFS problem and found the solution as a nonlinear first-order partial differential equation (PDF). This equation is known as the image irradiance equation and it is the basic equation for any SFS technique. It relates the image irradiance to the scene radiance as shown in Equation 1 below:

$$E(x,y) = R(\hat{n}(x,y)) \tag{1}$$

Where $E(x,y)$ is the image irradiance at a point (x,y), R is the reflectivity, and $\hat{n}$ represents the three components of unit surface normal.

As mentioned by Durou al. [5], the recovered surface can be expressed in four types; surface height (elevation) $z(x,y)$, surface normal (n_x, n_y, n_z), surface slope (p,q), and surface slant Φ and tilt Θ. The depth can be considered either as the relative distance from the camera or antenna to the surface points, or the relative surface height above the xy plane. This implies that equation 1 can also be written as follows:

$$E(x,y) = R(p,q) \tag{2}$$

where $(p,q) = (dz/dx, dz/dy)$, the first derivatives of height along x and y directions, respectively.

1.2 Radarclinometry

There are fundamental differences between the physics of SAR image formation and those of optical image. In fact, the reflectance characteristics and the geometry of SAR and optical imageries are highly different.

Mapping non flat regions of the Earth using SAR remote sensing can have improper radiometric corrections. The reason behind these effects is due to terrain variations (Freeman [6]). These effects are essentially the variation of local incident angles for every pixel from that of the flat Earth assumption of Geoid and the improper antenna pattern radiometric correction. Therefore, conventional SFS algorithm is not directly suitable to SAR imagery.

The major objection to RSFS is the ambiguity from uncertain backscatter properties. Involving some constraints like brightness, smoothness, and integrability can remove or reduce this ambiguity.

1.3 Smoothness constraint

It is more practical to pose SFS as a constrained minimization problem rather than purely an inversion one (Bors et al. [3]). Thus, minimization method obtains the solution by minimizing an energy function over the entire image. This function can involve some constraints, such as the smoothness constraint, the integrability constraint, the gradient constraint, and the unit normal constraint as well as the brightness constraint as a hard constraint (Jin et al. [8] and Du et al. [4]).
The smoothness constraint ensures a smooth surface in order to stabilize the convergence to a unique solution, and is given by:

$$\iint (p_x^2 + p_y^2 + q_x^2 + q_y^2)dxdy \qquad (3)$$

Here p and q are surface gradients along the x and y directions. Another version of the smoothness term is less restrictive by requiring constant change of depth only in x and y directions.

$$\iint (p_x^2 + q_y^2)dxdy \qquad (4)$$

The smoothness constraint can also be described in terms of the "surface normal".

$$\iint (\|\hat{n}_x\|^2 + \|\hat{n}_y\|^2)dxdy \qquad (5)$$

This means that the surface normal should change gradually.
The smoothness constraint is often formulated in terms of the directional derivatives of the recovered "surface normal". It is trivially minimized by a flat surface. Thus, the conflict between the data and the reflectance function leads to a strongly smoothened "surface normal" and the loss of fine details (Worthington and Hancock [16]).
Zheng and Chellappa [18] replaced the smoothness constraint by an intensity gradient constraint which is given by Equation 6 bellow.

$$\iint ((R_x - E_x)^2 + (R_y - E_y)^2)dxdy \qquad (6)$$

The purpose of the latter constraint is to overcome the over smoothness problem of the recovered surface. They computed the solution by minimizing an energy function, which involved the brightness constraint, integrability constraint and intensity gradient constraint over the entire image. Courteille et al. [3] improved the algorithm of Zheng and Chellappa [18] by adding proper occluding boundary (edge of the body in the input image) before applying SFS and adjusting the brightness error adaptively. Then, they applied the new algorithm to the surface height reconstruction of weld shape and showed that the accuracy had improved.

2. METHODOLOGY

a. Area of Study

The study area is the KASSALA state in the east of SUDAN. It lies between longitudes 35.59693ºE and 36.44708ºE and latitudes 15.11390ºN and 16.17869ºN. The most interesting features included within the area of study are ALGASH River and the TAKAH Mountain.

b. Materials

The materials for this study consist of one RADARSAT-1 image, covering the study area, and ground control points (GCPs). A subset from image of RADARSAT-1 was extracted to examine the performance of the smoothness constraint. The area of the subset was approximately 10 km^2. The purpose of choosing the subset was that it contained sufficient features to analyze and evaluate the performance of the algorithm. These features represented building, vegetation, water body and mountain. Thus, they provided a complex surface presentation, having a wide range between minimum and maximum surface elevations. Fig. 1 below represents a subset obtained from RADARSAT-1 S7 mode image. In this subset, the highest height values are located in the center of the figure.

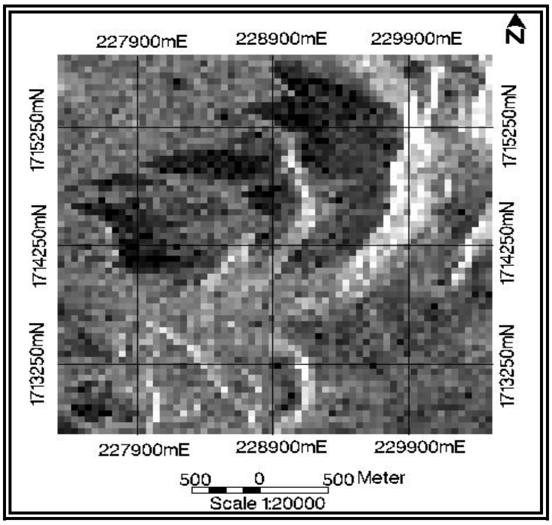

Fig - 1: Subset from RADARSAT-1 S7 Mode Image

c. Methodology

Digital image pre-processing was carried out to prepare the RADARSAT-1 SAR image first. Then the geometric correction was done to RADARSAT-1 image using some GCPs. After that the Radar brightness (β0) and backscatter coefficients (σ°) were calculated using equations 5 and 6, respectively.

$$\beta^o_{r,a} = 10 * \log 10((DN_{r,a}^2 + A3) / A2_r) \qquad (5)$$

$$\sigma^{o}_{r,a} = \beta^{o}_{r,a} + 10*\log10(\sin\theta_r) \quad (6)$$

Where:
$DN_{r,a}$ is a digital number at range (r) and azimuth (a),
A3 is a small constant (often 0),
$A2_r$ is a range dependent look-up table that contains a terrain type model.
θ_r is the incident angle at range (r).

Then, speckle filtering was applied to the backscatter coefficients to remove (or reduce) the speckle "inherent with radar data" from the image.

- ***Constraints***

As mentioned previously, minimization approaches of shape from shading obtain the solution by minimizing an energy function involving specific constraints over the entire image. In this paper, the smoothness constraint was involved. It ensures a smooth surface in order to stabilize convergence to uniqueness solution. The algorithm proposed by Brooks and Horn [2] and later developed by Mobarak [10] and [11] searches for the "surface slope estimates" that minimize the following cost function:

$$\varepsilon = \iint [(E(x,y) - R(\hat{p},\hat{q}))^2 + \lambda(\hat{p}_x^2 + 2\hat{p}_y^2 + \hat{q}_y^2)]dxdy \quad (7)$$

where,

E(x,y) is the observed image brightness values,

is the estimated predicted brightness values,

are the surface slope estimates along x and y directions,

are the second partial derivatives of Z(x,y), and

λ is a regularization parameter.

The second term of Equation 7 is the smoothness constraint, which overcomes the under-determined problem by ensuring that the obtained solution is unique. This constraint is very important when dealing with noisy data like radar imageries. The number of iterations and/or the regularization factor λ control the trade-off between the image details and smoothed surface estimates.

The steps of smoothing the surface estimates as follows:

- The calculation of the initial slope estimates for $(\hat{p},\hat{q})$ at every pixel in the image
- Smoothen the previous slope estimates $(\hat{p},\hat{q})$ to obtain a smoothed version of surface slope estimates.
- Evaluate the normalized reflectance function with the smoothened surface slope estimates to obtain the simulated radar SAR backscatter image at every pixel.
- Calculate the partial derivatives of the radar reflectance model, with respect to p and q at every pixel.
- Evaluate the calculated partial derivatives using the smoothened surface slopes.

3. RESULTS AND DISCUSSION

The objective of this section of the paper is to show and compare the performance of the smoothness constraint in term of number of iterations on surface heights recovery.

The performance of the constraint was tested on RADARSAT-1 image of Standard mode (S7). Evaluation was carried out qualitatively and quantitatively. Qualitative evaluation was conducted by investigating the shape of surface topography reconstructions and their actual values in the study area. Quantitative evaluation was done statistically through calculations of RMSE and R^2. Some 123 GCPs were used for this purpose.

In any iterative minimization SFS algorithm, the values of surface slope estimates were improved after each round of iteration. The values obtained after each round were input again as initial values for the next round of the iteration. The iterations continued until the termination condition was satisfied.
To analyse the effect of number of iterations, the produced surface height measurements versus the number of iterations were plotted as appeared in Fig. 2. The figure shows the filled contours (a) without iteration, (b) after 25 iterations, (c) after 50 iterations, and (d) after 100 iterations.
Visual inspection of this figure shows that increasing the number of iterations has reduced the errors arising from high relief terrain, meaning improvement of SFS height reconstructions. After 100 rounds of iterations, most of the surface heights were recovered. The range between minimum and maximum values of recovered absolute surface heights has increased from a small value of 420m for the absolute height reconstructions without iterations fig. 2-a to a large value of 600m, achieved after 100 iterations fig. 2-d. If the number of iterations exceeded 100, the minimum and maximum values of the recovered absolute surface heights would result in under-estimation and over-estimation, respectively compared to the actual heights.
It was observed also that the geometry of higher absolute surface values has moved through increasing number of iterations from lower-left corner to the correct locations at the centre. Another finding is that surface smoothing has increased with increasing number of iterations. It is obvious from fig. 2 that the noise has gradually reduced with increasing number of iterations.
The computation of RMSE and R^2 for various numbers of iterations is given in table 1. The RMSE values of 51.60m, 20.23m, 18.20m, and 17.49m and R^2 of 0.32, 0.942, 0.962, and 0.972 for 0, 25, 50, and 100 iterations, respectively are observed in the table. It is clear that the error of the absolute surface height reconstructions has reduced from 51.60m (with zero iteration) to 17.47m (with 100 iterations). Likewise, the correlation between the actual

and the estimated heights, indicated by R^2 has increased from 0.320 to 0.972 from zero iteration to 100 iterations. RMSE and R^2 obtained without iteration - 51.60m and 0.32 indicates very poor surface heights extraction. It is important to note that the values of RMSE and R^2 listed in Table 1 further support the results extracted from Fig. 2.

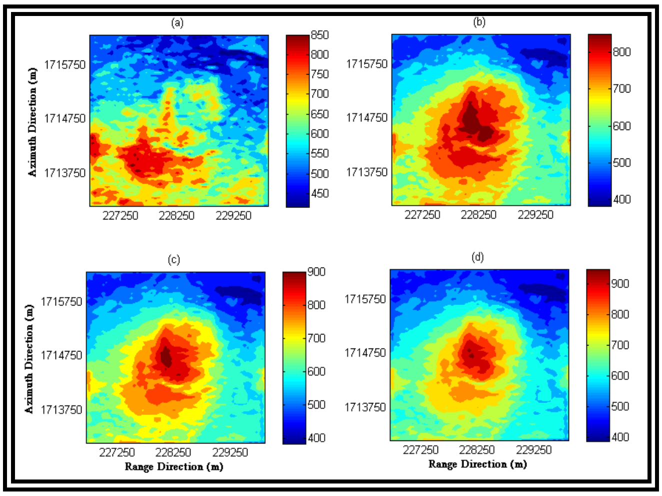

Fig. 2: The Effect of Number of Iterations on the Absolute Heights

Table 1: Effects of Number of Iterations on RMSE and R^2 of the Surface Height Reconstructions

Iteration	non	25	50	100
RMSE	51.60	20.23	18.20	17.47
R^2	0.320	0.942	0.962	0.972

The impact of the number of iterations on absolute surface height estimates was observed visually and numerically. As indicated in Fig. 2 and Table 1, the accuracy increases with increasing number of iterations. This is due to the fact that increasing the number of iterations has improved surface slope estimates after each round of follow up iterations. Consequently, the absolute surface height estimates have also improved. This is very important finding. That is, it overcomes the problem inherent with many SFS technique, which has suffered from low frequency component (large-scale surface variation) errors.

4. CONCLUSION

Smoothness constraint was tested in terms of the effect of the number of iterations. It was found that increasing the number of iterations has smoothened the surface slopes and consequently enhanced the final absolute surface heights. Very poor accuracy was obtained without any iteration with RMSE and R^2 of 51.60 m and 0.320, respectively, while the best accuracy was obtained after 100 rounds of iterations.

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BIOGRAPHIES

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