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SAR Image - Terrain Database Registration

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Abstract

The capability of estimating sensor platform position using SAR imagery, and a Digital Elevation Model (DEM) or a feature database has been the object of extensive research. Inertial Navigation System (INS) data is subject to drift, and it is assumed that no Global Positioning System (GPS) data is available. Two approaches to image-database matching are discussed in depth, along with some results using actual data. The first approach involves the use of a DEM to form simulated SAR images which are compared to the actual SAR image.

A second approach involves segmentation of candidate features from a SAR image and matching with possible corresponding features in a feature database. A particularly efficient data representation is used to eliminate features that are unlikely to be matched from the process. A logical extension of this problem lies in the decision of which features to choose from a feature database, given a particular SAR scenario. A rule based expert assistant for such a task is discussed.

Range differences in the images are used to estimate a correction to the estimated sensor position. A novel method of combining range differences to linearize the resection problem [Smith, 87] is used to simplify the estimation of the sensor position.

Introduction

Image to map matching or geocoding, is the process of assigning a geographic coordinate to each pixel of a sensed image. This task can be achieved in a number of ways. One approach involves computing an estimate of the sensor platform position and possibly the sensor attitude. This problem is called "resection in space" in photogrammetric terminology. In the past, resection in space has been achieved with computational procedures which relate individual pixel locations to ground control points with known geographical coordinates. These procedures are based on point to point correspondences. If enough individual control points are imaged and recognized, then such procedures are sufficient. However, often an imaged scene does not contain the signatures of sufficiently many individually recognizable control points, but rather contours of known objects.

Within this scenario, the flight log for actual SAR missions is based upon INS, and GPS data is not available. We use the flight log data as the original estimate of platform position. Since, INS is subject to drift, our original estimate of platform position is subject to a finite, but random error. Hence, the match and resection operations must account for and correct this error.

The first approach described below is based upon exploitation of contour to contour correspondences. We selected terrain induced shadows in SAR images because they are definitive and relatively static contours for use in matching with Digital Elevation Model (DEM) based simulated SAR imagery. The method presented consists of a two stage matching algorithm. The first stage consists of a classical area correlation used to provide a better approximation of matching locations and reduce error from the original platform position estimate provided by flight data. The second stage consists of an exact point to point matching based upon corresponding shadow contours in the actual and simulated SAR images.

The second approach is based upon matching of feature data. Clearly, the extraction of features in the sensed imagery should not proceed independently of knowledge represented in feature databases, and any approximate knowledge of sensor platform position. Unguided segmentation based solely on image luminance values has long been known to lead to problems because the object and intensity boundaries are not always the same. The approaches generally taken can be classified into two areas, namely region-based, and boundary-based. The method presented utilizes a combination of classically region-based correlation and boundary-based matching on preprocessed SAR and photographic imagery, and produces a rank for comparison of the goodness of matches. The particular representation of the feature boundaries allows fast and efficient feature matching. This method was demonstrated using National High Altitude Photography (NHAP), and the preprocessing required for SAR imagery was investigated.

Particular features must be chosen from a feature database for matching to the image. A rule-based system for choosing data from a feature database provides a logical extension for automation of the feature matching process. The immediate goals of such a system would include choosing features that would be likely candidates for matching in an image, as well as weighting chosen features according to several preselected criteria.

Once a point to point correspondence is determined, either by shadow matching or feature matching, the resection in space can establish the platform position. Since the resection generally consists of a non-linear system of equations, a method of employing range differences to linearize the problem is applied, and the system simplifies to one that can be solved by the generalized inverse solution.

Matching Using Simulated SAR Imagery

In the particular case when GPS data is not available, and not enough control points are available for a resection in space to be successfully computed, additional data must be found in order to accurately determine platform position with the resection procedure. In this section, we describe a method that employs contour to contour matching using terrain induced shadows in radar imagery to augment or replace control point data to improve accuracy of the subsequent resection in space.

The method requires the availability of a DEM from which a simulated radar image is created using the flight log parameters from the radar mission. These parameters which generally consist of an approximate straight line flight path will

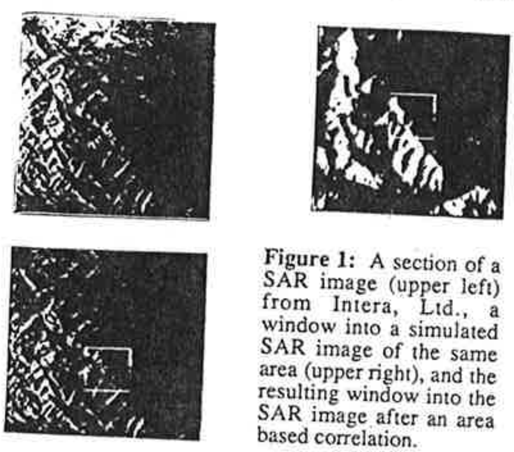

Figure 1: A section of a SAR image (upper left) from Intera, Ltd., a window into a simulated SAR image of the same area (upper right), and the resulting window into the SAR image after an area based correlation.

act as the initial estimate of the platform position. Also, it is assumed that the actual flight direction is known to within one degree, so that rotational effects are negligible. The range and azimuthal resolution of the DEM and the radar image must be comparable. A two stage matching algorithm is then employed between the simulated and actual radar images.

The first stage of the algorithm involves an area based correlation between a subsection of the actual SAR image that is known to contain terrain induced shadows, and a section of the simulated image. Figure (1) illustrates this step using STAR-1 SAR imagery from Intera Ltd. of Calgary, Canada, and a simulated SAR image created at VEXCEL. The subsection of the SAR image can be determined from analysis of the DEM using the radar flight parameters to determine reasonable areas in which to find terrain induced shadows. The subsection of the simulated image is determined by the amount of error expected in the initial estimate.

In our experiments, we used the entire simulated image for correlation, assuming that the error could be as much as half the image size. A hierarchical form of correlation was used that employed a sequence of matches on a pyramid of reduced resolution versions of the real and synthetic images taken along the approximate straight line flight path described by the initial estimate. Coarse registration is performed at the coarsest resolution, leading to finer adjustments on higher resolution versions of the imagery [Rosenfeld, 84].

Both normalized correlation, and sum of absolute differences correlation [Barnea, Silverman, 72] were tested for the area based correlation scheme, with similar results. The sum of absolute differences correlation was possible because the radar simulation incorporates a radiometric equalization with the actual SAR image histogram. Also, the sum of absolute differences metric proved to be more computationally efficient than normalized correlation and thus would be the method of choice. Since rotational inaccuracies are very small, the area based correlation can generally bring the actual and simulated images to within a few pixels of each other, but not close enough for precise pixel to pixel matching to be successful.

The next step uses contour to contour matching in order to achieve a point to point correspondence between the simulated and real images. Since the simulated image was created from the DEM by a known process, once the actual SAR image is matched to it, the pixels of the SAR image are, in essence, known in DEM coordinates. The resection can then be used to determine the sensor platform position in the DEM coordinate frame. Such a resection carries out at sufficiently small steps along the flightpath can provide an incremental correction to the INS data such that a more exact flightpath can be determined.

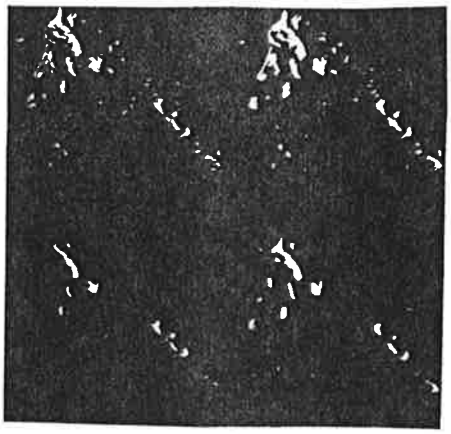

Figure 2: A comparison is sigma filter images. The original SAR image (upper left) and increasing values of sigma for smoothing: σ=0.15 (upper right), σ=0.30 (lower left), σ=0.45 (lower right).

The second stage of the algorithm involves matching the outlines of the shadows within the correlated areas in the actual and simulated images. First, the shadow outlines must be extracted from each image. No speckle noise is added to the simulated radar images, therefore, the shadow outlines can be extracted by thresholding the image at zero, and employing an edge following algorithm to vectorize the shadow outlines.

Shadow segmentation in the real SAR image is based upon the inherent bimodality of the local histogram in the correlated shadow region. When noise and speckle content is high, however, this bimodality can be corrupted. In such cases, the modality is restored using nonlinear preprocessing to preserve shadow edges and smooth noise. An example of such processing is nonlinear speckle suppression using sigma filtering [Lee, 83]. See Figure (2). This can also be viewed as an edge interest operator.

The SAR image is then thresholded at the gray value corresponding to the minimum in the bimodal histogram, and the shadow edges are vectorized with an edge following algorithm. Next, the vectorized edges in each image are encoded in $\Psi(s)$ representation. The $\Psi(s)$ representation encodes a two dimensional polygon into a one-dimensional function by taking the local tangent angle as a function of the arc length [Ambler et al. 75]. Making the arc length sufficiently large results in a smoothed $\Psi(s)$ function. This provides a simply way to remove pathological small perturbations in the shadow contours.

Clearly, the points of highest curvature along any given polygon will be given by the zero crossings of the second derivative of the $\Psi(s)$ function. We found

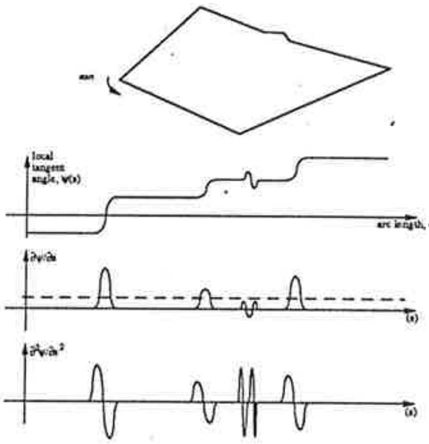

Figure 3: Thresholding for the maxima of the first derivitive of the $\Psi(s)$ function allows for extraction of points of highest curvature, and avoids small scale roughness in shadow contours.

however, that for the case of terrain induced shadows, the actual vectorized contours are somewhat ragged. Hence, the zeros of the second derivative pinpoint every inflection in curvature around the contour. In order to extract only the points of sharp tangent angle changes, the first derivative of the $\Psi(s)$ curve was thresholded for sections of maximal curvature fluctuation. The median of each thresholded section was taken to be the point of highest curvature. In this way, only points along the contour at which the tangent changed sharply would be extracted. See Figure (3).

This $\Psi(s)$ function represents the angular measure of the local tangent described by the derivative with respect to the arc length of the vector function defining the curve. Since curvature is associated with the second derivative, we see that the maxima of curvature occurs where $\Psi'(s)$ is maximum.

This process was carried out for both the actual and the simulated SAR images. Finally, points in the simulated and actual SAR images are matched based upon their locations within the corresponding correlation windows, as well as their angular locations with respect to one another. See Figure (4).

Next the simulation procedure which led to a ground range radar projection is reversed, and the matched pixels in the SAR image are assigned coordinate locations in the DEM reference frame. A resection in space can be calculated to yield and estimate of the platform position. A small error will occur because the association of SAR image and DEM points is dependent on occluding points for shadows. If the sensor position changes, the occluding points change slightly. However, this is a second order effect which may be successively reduced if the estimation process is repeated by iteration on the new estimated sensor position.

Matching Using Feature Database

Another method for determining ground control points involves the use of imaged feature data. This method is particularly useful when a DEM is not available, or not sufficiently accurate, but flight data from the imaging mission is still suitable for an initial estimate. For large scale implementation of a feature matching method, a digitized feature database such as the DMA Digital Landmass Database, is required. For the purpose of experimentation, we utilized DMA Digital Feature Analysis Data (DFAD) in a region approximating the actual imagery we tested.

Figure 4: Points of highest curvature in the real SAR image (upper left), and the simulated SAR image (upper right). Graphical representation of matched points along shadow contours in real and simulated images (lower left).

Classically, feature matching algorithms are either region based, or boundary based. The method presented here is a combination of both types. First a boundary extraction and segmentation is applied, then a template oriented correlation matching metric is used to find the best boundary to match the imaged feature.

DMA Digital Feature Analysis Data consists of four types of features: point data, collections of points, lineal data, and areal data. All four types consist of lists of points in geographic coordinates which, for the latter two types, when linked together by straight lines describe a feature by a polygonal approximation.

The appearance in an optical image of such a polygonal approximation will be modified by a perspective transformation. A ground range SAR image will similarly have some distortions if the feature lies in terrain relief.

The feature matching procedure explored, used NHAP data which exhibited a negligibly small amount of perspective distortion. The method itself involved an efficient search for one particular arbitrarily chosen lineal or areal feature. In a fully automated system, the initial feature used in the matching would be chosen by a rule-based expert assistant. This idea is discussed more fully in the last section.

Once the initial feature was chosen, the optical image was preprocessed using the Sobel edge operator [Pratt, 78], and thresholded at two standard deviations above the mean gray value to produce a binary image containing the major edges. We found that images processed with the Sobel edge operator tended to exhibit a log-normal histogram. The micro-edges tended to occupy the lower "less bright" gray values, while the major edges generally due to outlines of major features, were brighter. The thresholding step removed the micro-edges, leaving only the bright major boundaries in the binary image. Isolated pixels were then deleted, completing the preprocessing of the imagery.

Next, the DFAD was converted to image coordinates from geographic by a linear transformation given the resolution of the image. The selected feature was stored as a list of pixel coordinates extending between the transformed DFAD coordinates that described it. The raster coordinates along the feature were then subsampled to produce a mask, which was subsequently correlated with the binary edge image using sum of absolute differences correlation [Barnea, Silverman, 72]. The correlation was carried out only at locations in the edge image where the first pixel of the feature mask fell on a bright pixel, thus increasing computational efficiency of the operation. The top three locations of correlation maxima were retained, and the full feature pattern was then correlated at those locations to produce the best estimate. Localized edge detection was then employed to produce better estimates of the original DFAD tie points and the image. Once one feature was matched, a localized method could be applied to features throughout the image to gain multiple tie points, leading to a resection operation.

Presently, a human must intervene in the above operations to choose the initial feature and to resolve conflicts during the correlation steps. Therefore, the development of a rule-based expert assistant is a logical step toward automation of this process. The groundwork for such a system is described in the last section.

Linearization of Resection Problem Using Range Differences

A novel method of combining range differences borrowed from a method used in sonar [Smith, 87] is used to simplify the estimation of the sensor position. The technique was originally developed to localize a single source given a set of noisy range difference measurements. This is ideally suited to our problem in that it should be assumed that some error is associated with all matched ground locations, as well as range data. The method is derived from linear least squares estimation theory, and approximates the maximum likelihood estimate without requiring the more rigorous solution to the system of nonlinear equations provided by a classical resection in space.

The scenario assumes that the direction of the flight path is known to sufficient accuracy, that the INS positional errors for the imaging period give good relative positional estimates, and that what is required is an offset estimate in crossrange and altitude for each azimuthal section of an image. Thus, if an exact flight path were required, an offset would have to be computed for each range line of an image. This offset, of course, must be based upon data from range lines around the particular line of interest.

Given that N ground locations were matched, we set up the problem as follows:

$$\begin{aligned}
\bar{x}_s &= \text{sensor position} \\
\bar{x}_i &= \text{row vector, known ground locations, where } i = 1, \ldots, N \\
c_i &= |\bar{x}_s - \bar{x}_i| \\
\Delta c_{ij} &= c_i - c_j, \text{ where } j = 2, \ldots, N \\
M &= 3 \times N \text{ matrix of } \bar{x}_i \text{ vectors}
\end{aligned} \tag{1}$$

Letting $\bar{x}_1$ arbitrarily be the origin point for range difference computations, the following scalar and vector values are computed.

$$\begin{aligned}
r_s &= |\bar{x}_s| \\
\bar{v} &= (r_2{}^2 - \Delta c_{21}{}^2, \ldots, r_N - \Delta c_{N1}{}^2)^T \\
\overline{\Delta c} &= (\Delta c_{21}, \ldots, \Delta c_{N1})^T
\end{aligned}$$

The approximate least squares estimate according to Smith is given by:

$$\bar{x}_S = \frac{1}{2}(M^T M)^{-1} M^T(\bar{v} - 2r_S\overline{\Delta c}) \tag{2}$$

This is simply the generalized inverse solution to the minimum least squares value for $\bar{\varepsilon}^T\bar{\varepsilon}$, where $\bar{\varepsilon}$ is given by:

$$\begin{aligned}
\varepsilon_i &= r_{i2} - \Delta c_{i1}{}^2 - 2r_s\Delta c_{i1} - 2x_i{}^T x_s, \; i = 2, \ldots, N \\
\bar{\varepsilon} &= (\varepsilon_2, \ldots, \varepsilon_N)^T
\end{aligned}$$

This solution closely approximates the maximum likelihood solution for sensor location, and could be used as a starting estimate to iteratively compute the maximum likelihood solution to the nonlinear resection equations. Such a procedure is virtually certain to converge quickly with a good starting estimate given by the linear procedure above.

We can generalize this result to incorporate INS measurements, again assuming that an estimate in crossrange and altitude is required. Using the INS measurements, we compute the following values:

$$\begin{aligned}
t_i &= \text{the time points corresponding to a range measurement with respect to an identified DEM position} \\
p(t_i) &= \text{the set of INS measurements for the time points } t_i, \text{ where } i = 1, \ldots, N \\
\bar{x}_o &= \text{the desired INS offset}
\end{aligned}$$

Then modify one of the definitions of Eqn. (1) as follows:

$$\begin{aligned}
c_i &= |p(t_i) - (\bar{x}_o - \bar{x}_i)| \\
&= |\bar{x}_o - (\bar{x}_i - p(t_i))|
\end{aligned}$$

Therefore, one can use the generalized inverse solution (Eqn. (2)) to obtain the INS offset but with $\bar{x}_i$ replaced by $(\bar{x}_i - p(t_i))$.

The accuracy of this resection operation is limited by the resolution of the imagery, and the resolution of the terrain or feature database. The INS compensations to the SAR phase history are also assumed to be good such that the INS can

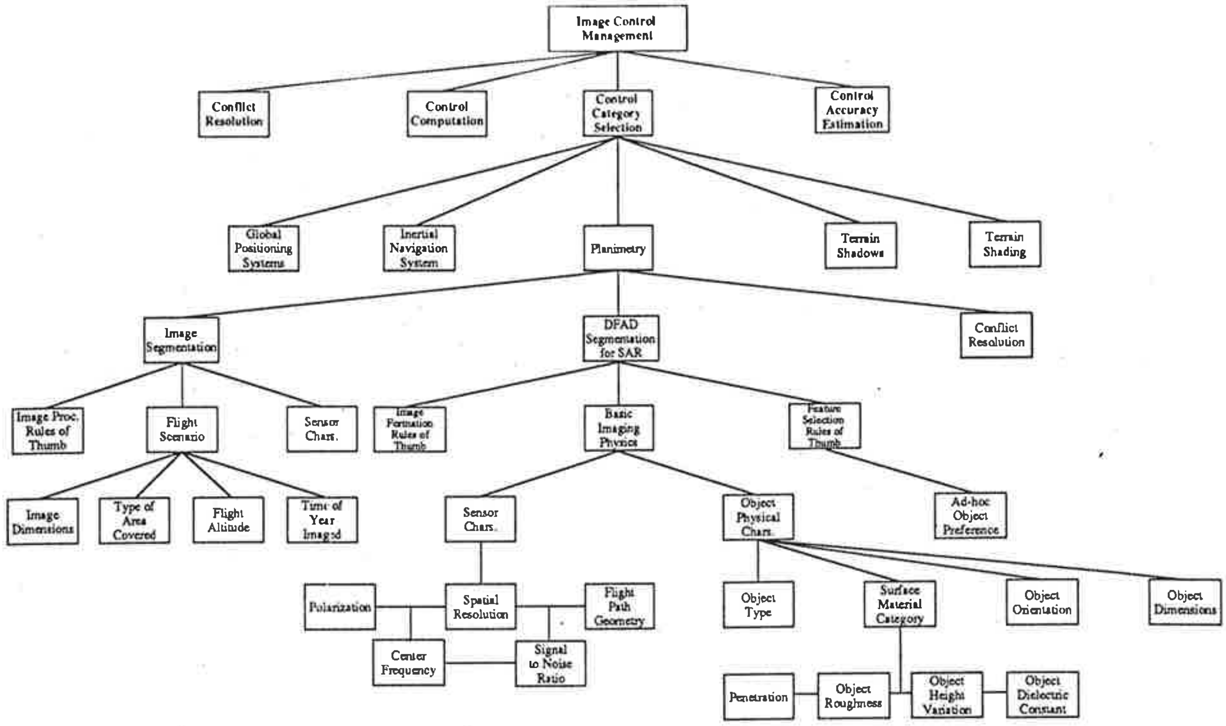

Figure 5: Hierarchical organization for rule base for feature segmentation.

be used as a basis for a more precise description of the platform flightpath. Also, in order for a resection operation to be convergent, the ground control points must be located in a relatively wide area in the image. That is, a small cluster of points will lead to an ill-conditioned resection, and poor results.

The least squares solution given in Eqn. (2) above can be generalized to include a weighting matrix W, by replacing M^T by M^TW.

Expert Assistant for Feature Data Segmentation

A rule-based feature segmentation system would be only a part of an overall strategy for utilizing INS, GPS, and terrain induced shadow, and shading data, to determine platform position. Such a system would be somewhat misnamed as an "expert system", since an argument may be given that whenever one is operating strictly according to rules, one is actually operating at the level of an advanced beginner. A real expert, on the other hand, is able to create new rules based on experience, modify and find appropriate exceptions to existing rules, and make novel hypotheses. However, a reasonable and achievable rule-based system could be developed to carry out simple tasks and make routine choices. The output from such a system is potentially very helpful in average situations that do not require any extraordinary interpretation by a human expert in radargrammetry. We shall term such a system an "expert assistant".

In the case of feature segmentation for matching to a given radar image, the assistant would be required to choose initial features, choose appropriate image processing, and resolve conflicts throughout the process. It would also decide which procedural modules to execute, and would evaluate their outputs using its knowledge base. The rules making up the knowledge base must be based on the physics of the imaging scenario, as well as heuristics, and "rules of thumb" commonly employed by practicing experts. It is important to organize the rules in a hierarchical fashion. Figure (5) shows the hierarchical structure by which we have developed an initial rule base.

The subgoals of such a system would include weighting chosen features according to several criteria. These may include the expected visibility of the feature, and its distinguishability from others that are similar to it, as well as from its background. The predictability of the features appearance, and the complexity of the matching process should also figure into a composite score for the feature. Once all the criteria have been evaluated for each candidate feature, a rank list can be created of the most likely and productive features for a matching process.

Conclusions

We have demonstrated that digital terrain and feature data can be combined with automated image matching techniques to provide ground control information suitable for determining SAR sensor platform position using resection in space. This method finds local corrections for INS data which is subject to drift, and is applicable when GPS is not available.

The limitations of the resection accuracy are due to the image resolution, the faithfulness of the INS compensations into the SAR phase history processing, the accuracies of the features in the database, and the numerical stability of the resection geometry.

One of these methods uses image processing techniques to automatically extract and match radar shadows from a SAR image with the predicted shadows that are consistent with and estimated sensor location relative to a terrain model.

Efficient methods were also developed for locating arbitrary planimetric features in a SAR image for the purpose of matching with a digital feature database. These matched features were also used for resection. Present efforts now focus on the development of a rule-based expert assistant to aid in the selection of appropriate planimetric features for such matching.

References

1. J.O. Smith, and J.S. Abel, "Closed-form least-squares source location from range-difference measurements", *IEEE Transactions on Acoustics, Speech and Signal Processing, Vol. ASSP-35*, 12, 1987, 1661-1669.
2. Rosenfeld A., ed. *Multiresolution Image Processing and Analysis*, Springer Verlag, 1984.
3. D.I. Barnea, and H.F. Silverman, "A class of algorithms for fast digital image rectification", *IEEE Transactions on Computers, Vol. C-2*, 2, 1972, 179-186.
4. J.S. Lee, "Digital image smoothing and the sigma filter", *Computer Vision, Graphics, and Image Processing, Vol 24*, 1983, 255-269.
5. A.P. Ambler, H.G. Barrow, C.M. Brown, R.M. Burstall, and R.J. Popplestone, "A versatile system for computer controlled assembly", *Artificial Intelligence,Vol. 6*, 2, 1975, 129-156.
6. Pratt W., *Digital Image Processing*, John Wiley & Sons,1978.