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EVALUATION OF LOCAL AND GLOBAL DEFORMATION MODELS FOR THE REGISTRATION OF SIMULATED SPOT IMAGES

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I. ABSTRACT

Two aircraft gathered simulated SPOT images were precisely registered using local deformation models. The models do a local least squares fit at each point of a resampling grid. Mean registration errors of less than one pixel are achieved.

II. INTRODUCTION

Satellite images are being used more and more for land use studies and urban area management. In urban areas, such studies have been limited by the coarse resolution of the available data. Two high resolution, temporally separated images of Simulated SPOT data of West and South-West Paris were gathered to evaluate their use in an urban study (Laine, Ballut and Nguyen 1983).

These images will be used to:

- o identify the different land use units,
- o follow their temporal evolution,
- o develop a computer assisted cartographic procedure to generate and update urban land use maps by applying advanced image processing techniques.

From experience, the change of land use pattern in the region of Paris is about 0.5 % in area per year, and if these changes could be detected by remote sensing instead of field work, significant savings would result. To detect the changes, the data need to be very accurately registered. The purpose of this paper is to present registration results using different geometric deformation models.

For the simulated SPOT data, acquired from an airborne scanner, a global polynomial deformation model similar to those often used to correct satellite images, is not accurate enough. Instead of using a single deformation model for the whole image, we have investigated methods of using models which are locally computed by a least square fitting using the nearest control points.

III. THE SIMULATED SPOT DATA

The data used in this study is simulated SPOT data (GDTA 1983) produced by GNTA (Groupement pour le Développement de la Télédétection Aéroportée). The data is simulated from an airborne Daedalus scanner. One image was taken in September 1981, and the other in March 1983

(Figure 1). In the simulated SPOT data, four bands are available, three narrow spectral bands having 20 meter resolution, and one panchromatic (0.51 to 0.73 μ m) band with 10 meter resolution. All work for this study used the 10 meter panchromatic band.

IV. REVIEW OF LOCAL MODELLING METHODS

Geometric correction of digital image data requires a model of the deformation to be applied. The model may be global (one model for the entire scene) or local (a set of models, each one valid in a portion of the scene). Local models are necessary when high frequency deformations exist in the image data. Examples of high frequency deformations include:

1. Alignment errors in linear array sensors.
2. Errors introduced by the irregular flight trajectory of low altitude aircraft mounted sensors.
3. Displacements due to terrain elevation variations when the incidence angle of the sensor is high. This is often present in radar imagery.

In using and applying local models, problems that must be solved include partitioning the input image into regions over which separate local models will be computed, deciding on the form of the local models, and guaranteeing continuity of the models at the region boundaries. Techniques that have been used to model the local deformations include:

1. Voronoi tessellation which divides the image into triangles defined by the control points. Each triangle is deformed by a linear model computed using the three control points (the vertices) of the triangle, adjusting the sides with Spline function (Deviljver 1982, Fortin 1983).
2. Elastic models which consider the image as an elastic material. By applying external forces, the geometry of the image is changed to become similar to the desired output. (Bajsy 1982, Broit 1981).
3. Physical models such as a model of the aircraft flight trajectory. In this case, the regions over which separate models are defined may be selected in advance based on sensor characteristics. (Jeansoulin 1981). In general, the physical model methods give better results with fewer control points, but can only be applied to the case modelled, and not extended to other images.

4. Direct least squares fitting to the control points, but repeating the fit in different areas of the image, and limiting the points used to those that are near the region. This is the method described in this paper.

V. GEOMETRIC REGISTRATION METHOD

Geometric registration of two images, whether using global or local deformation models, generally involves three steps: finding control points in the two images, modelling the deformation using the control points, and then resampling.

In our work, the control points were found by locating them with a cursor in side-by-side displays of the two images on a high resolution monitor (the IBM 7350). Deformation models are sensitive to the number and distribution of the control points. To ensure a good distribution on the whole image (512 x 1024), it was divided into a set of 4 horizontal by 8 vertical blocks, each 128 lines by 128 pixels. At least 5 points were located in each block. In this way, we selected 190 control points well-distributed over the image. All models presented later used all 190 points.

The methods for modelling the distortion from the control points is the main subject of this article and is described in the next section. Here we describe resampling and the "resampling grids" generated from the models which control the geometric distortion applied.

Our resampling algorithm takes as input an image and a set of grids, one grid defined on the output image, the other on the input image. A set of line coordinates $(L(i), i=1, \dots, n_l)$ and a set of pixel coordinates $(P(j), j=1, \dots, n_p)$ are defined on the output image, and the output grid is the cross product of $L(i)$ and $P(j)$. The input grid consists of a set of line and pixel coordinates $(H(i,j), K(i,j))$ in the input image where $H(i,j)$ is the line coordinate corresponding to output grid point $(L(i), P(j))$, and $K(i,j)$ is the pixel coordinate. $H(i,j)$ and $K(i,j)$ are computed by applying the distortion model to the point $(L(i), P(j))$ of the output image.

The resampling algorithm uses a spatial bilinear interpolation between the input grid points to locate the positions at which to resample. Thus the grid points are defined to be sufficiently close together to avoid positional errors due to the bilinear interpolation. In the examples in

this article, the grid points were located approximately every 10 lines and every 10 pixels. The radiometric value of each pixel in the output image is then computed by a cubic convolution interpolation using 16 points.

VI. DESCRIPTION OF THE MODELLING TECHNIQUES

Global models. Global models are generally accurate enough for satellite imagery. A global model, which consists of two polynomials (one for line and one for pixel), is computed by a least square fit to the control points on the entire image. Thus the coefficients $\langle c \rangle$ of the polynomials are computed to minimize

$$\| M \langle c \rangle - \langle x \rangle \|^2$$

where the element $m(i,j)$ of matrix M is the product of the variables of the j th term in the polynomial using the i th control point coordinates in the reference image (in our case, September 1981), $\langle c \rangle$ is the vector of polynomial coefficients to be computed, and $\langle x \rangle$ is the vector of control point coefficients in the input image (March 1983). The degree, and terms of the polynomials may be varied, points with high residual errors from the fit eliminated, and "test points" used to check the accuracy. The global polynomials are used to map each point in $L(i) \times P(j)$ to produce the input grid, and these are passed to the resampling algorithm. As a basis for comparison, we computed global polynomials up to degree 5 to model the deformation between the two SPOT images. As shown in Table 1, they did not approximate well the deformation.

Unweighted local models. The local modelling method consists of computing a new polynomial $\langle c \rangle$ at each grid point and using this local model to map the grid point coordinates to the input image. Each model uses only the n nearest control points to the grid point. Again, each model is composed of two polynomials (horizontal and vertical). The degrees of polynomials and the number of control points n may be selected. (The same values are used for all models in an image.) Thus we can modify the deformation influence area around each resampling grid node.

Weighted local models. We added a weighting function to the least squares fit for the local models. For each grid point, the polynomials $\langle c \rangle$ are computed to minimize

$$\| W (M \langle c \rangle - \langle x \rangle) \|^2$$

The control points are weighted as a function of their distance from the grid point. W is a diagonal matrix with

$W(k,k) = 1/d(\text{control point } k, \text{grid point})^{2e}$
 where e is a selectable exponent, and $d(.,.)$ represents the distance function.

In all the local models, certain parameters have to be specified:

1. The number of control points n used in each fitting to determine the spatial influence of local deformation around a grid point,
2. The degree of the polynomial.

For the weighted models, two additional parameters are:

1. The exponent e of the distance to use. The larger e , the more weight given to closer points. We used $e=0.5$.
2. To avoid very large weights for any given point, a minimum distance threshold was used. The distance for any point less than the minimum was replaced by the minimum. We used a minimum of 2.

To compare the methods, we ran the following test cases:

- o Global models of first, second, third, and fifth order.
- o Local first order model with 5, 7, and 10 control points, unweighted.
- o Local second order model with 7, 10, and 13 control points, unweighted.
- o Local third order model with 15 control points, weighted by their distance from the output grid point.

VII. EVALUATION OF THE RESULTS

In order to judge the registration accuracy, we used several methods of evaluation:

1. Visual observation in which the original image (September 1981) is displayed in yellow and the deformed image (March 1983) in blue. Perfectly registered areas will appear in white, whereas those badly registered will have either yellow or blue color.
2. The mean RSS error of registration. The mean RSS error in the control point locations is computed by comparing the locations of the control points as found manually with their locations as they are mapped by the resampling grids. Let (l_r, p_r) and (l_i, p_i) be the line and pixel coordinates of a control point in the reference and input

Images. If the modelling were ideal, and no errors were introduced by the spatial bilinear interpolation used between the input grid points, location (l_r, p_r) would be mapped exactly to (l_i, p_i) using the grids. The actual residuals, for example, the line residuals r_l , are computed as $r_l = l_m - l_i$ where l_m is the line coordinate of (l_r, p_r) mapped using bilinear interpolation between the input grid points. The RSS is the square root of the sum of the squares of r_l and r_p (the residue in pixel). Table 1 lists the mean of the RSS values for all control points for different modelling methods.

3. The coefficient of correlation between the two images. Well-registered images will

have a high correlation coefficient. Values are listed in Table 1. This can also be judged by analysing the form of the 2D histogram of the two images (Figure 3). Well-registered images will have a narrow scatter plot lying along the diagonal.

4. Difference images of the reference image and the registered image, shown in Figure 2. The difference images are computed as:

$(\text{September 1981}) - (\text{March 1983}) + 128$
 where the 128 is used to scale the output to be a middle grey in areas of no difference. Examples of the differences in the quality of the registration can be seen in the road alignments in the areas marked A and B in Figures 2a, 2b, and 2c.

Registration Method			Correlation Coefficient	Mean RSS Error of Registration
Local Model (equally weighted points)	1st degree	5 pts	0.5428	1.98
		7 pts	0.5174	2.50
		10 pts	0.4853	2.96
	2nd degree	7 pts	0.5307	0.89
		10 pts	0.5423	1.60
		13 pts	0.5417	2.05
Weighted Local Model	3rd degree	15 pts	0.5565	0.50
Global Model	1st degree		0.3112	10.27
	2nd degree		0.3156	9.25
	3rd degree		0.3439	6.40
	5th degree		0.4246	3.79

Data : Simulated SPOT data
 Band : panchromatic (10 m resolution)
 Size : 1024 lines x 516 pixels
 Total Number of Ground Control Points : 190

Table 1. Comparison of registration accuracy

VIII. DISCUSSION AND CONCLUSIONS

For the case we studied--data gathered by an airborne Daedalus scanner--visual observation and the numerical results listed in Table 1 show that the local models are clearly better than the global models. Between the different local models, it is difficult to see the difference visually, but the quantitative results--correlation coefficient and mean RSS error--indicate that the weighted local model gives the best results in the sense that it best follows the located control points. However, the more local the model, or the more weight given to closer points, the more sensitive the models become to control point accuracy and distribution.

An advantage of these methods is that they do not produce artificial boundaries on the output image as can appear with other local methods (Voronoi tessellation or methods where regions are selected in advance). Also the methods require no physical model and can be applied whenever there are sufficient control points. The disadvantage is that many control points are required, and the repeated fitting is relatively expensive in terms of computation time.

In our models, the "closest" control points were those closest in distance. An alternate method would be to select those closest in time--that is, to try to select those observed in the same or adjacent scans of the sensor. This could lead to a better physical model of the imaging system, and thus allow better interpolation or extrapolation of the deformation models into areas with no nearby control points.

All work here was motivated by the requirements for using the data in an urban study. In this

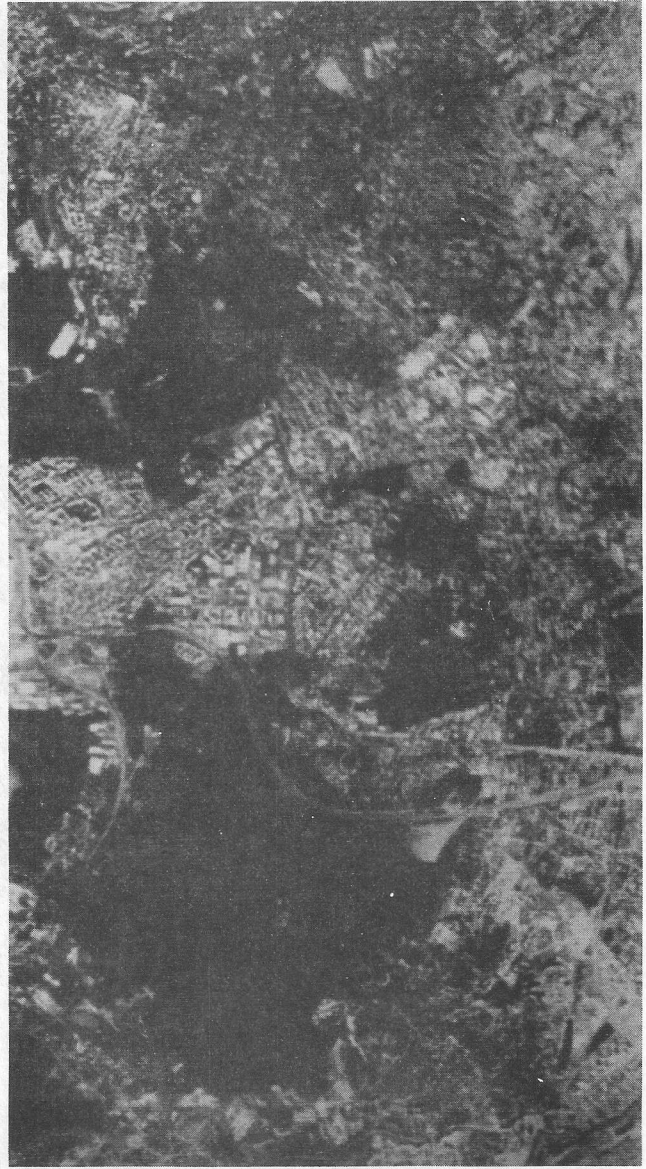
case, RMS errors in the range of about 1 pixel are satisfactory considering the complexity of the deformation in the airborne data, and are accurate enough to detect the land use change in the region.

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September 1981



March 1983

Figure 1 Original images of the panchromatic band



(a)
Global 5th degree



(b)
Local 1st degree no weight

Figure 2 a & b . Difference Images

is similar to the one in Figure 1. The difference image is shown in Figure 2c. The difference image is shown in Figure 2c. The difference image is shown in Figure 2c.



(c)
G Local 3rd degree with weight

Figure 2c . Difference image

Author biographical data

Martine Fortin received a degree in Electrical Engineering in June 1987, a master's degree in Digital Information Processing, Pattern Recognition and Artificial Intelligence in June 1988, and a Ph.D. in Remote Sensing in 1991. She is currently an associate professor at the University of Paris, France. She joined the ISE Paris Scientific Center in Paris as a student in 1987 where she worked on registration algorithms. She is now an engineer at SEP working on multi-source image registration, particularly with thematic maps.

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Figure 3 . Two dimensional histogram of corrected 83 images versus the original 81 image.

Author biographical data

Martine Fortin received a degree in Electrical Engineering in June 1980, a Master's degree in Digital Information Processing, Pattern Recognition and Artificial Intelligence in June 1981 (University of Paris), and a PhD in remote sensing in 1983 (University of Paris, thesis subject on Multi-Source Image Registration). She joined the IBM Paris Scientific Center in Paris as a student in 1981 where she worked on registration algorithms. She is now an engineer at SEP working on multi-source image registration, particularly with Thematic Mapper data.

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W. Niblack received a B. S. degree in Physics from Georgia Tech (1970) and an M. A. in Mathematics from Texas (1976). He joined IBM in 1973 where his work included development and implementation of image processing algorithms and systems. He was the analyst for the NASA contract for the development of the CPLRS, the system used to find control points in Landsat MSS and RBV data. In 1979, he joined the IBM Science Center in Paris where he was the software architect and later manager of the development of the High Level Image Processing System (HLIPS), a software system for the IBM 7350.

E. Boquet has a B.A. and M.A. degrees from the University of Paris (Paris VII) in geography. She has done research on the potential use of the SPOT simulation data for urban planning in an IBM France/IAURIF (Institut d'Amenagement et d'Urbanisme de la Region Ile de France) joint study.