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SPOT stereo matching for Digital Terrain Model generation

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ABSTRACT
This paper presents a matching algorithm for automatic Digital Terrain Model (DTM) generation from SPOT satellite images that provides dense, accurate and reliable results and attacks the problem of radiometric differences between the images. The proposed algorithm is based on a modified version of the Multiphoto Geometrically Constrained Matching (MPGC). It is the first algorithm that explicitly uses the SPOT geometry in matching, restricting thus the search space in one dimension, and simultaneously providing pixel and object coordinates. This leads to an increase in reliability, and to reduction and easier detection of blunders. The sensor modelling is based on Kratky’s polynomial mapping functions to transform between the image spaces of stereopairs. With their help epipolar lines that are practically straight can be determined and the search is constrained along these lines. The polynomial functions can also provide approximate values, which are further refined by the use of an image pyramid.

Radiometric differences are strongly reduced by performing matching not in the grey level but in gradient magnitude images. Thus, practically only the information in stripes along the edges is used for matching. Edges that exist in only one image can be detected by subtracting quasi registered images in the upper levels of an image pyramid. The points to be matched are selected by an interest operator. Gross errors can be detected by statistical analysis of criteria that are provided by the algorithm and by a robust analysis of the heights within local neighbourhoods.

The results of an extensive test using a stereo SPOT model over Switzerland will be reported. Matching with different options and the qualitative comparison of the results based on thirty thousand check points will be presented.

1. INTRODUCTION
SPOT is the major operational satellite with ensured continuity that provides stereoscopic coverage of the earth, and thus permits derivation of DTMs on global scale. Various matching algorithms for automatic derivation of DTMs from SPOT images and accuracy tests have been published in Angleraud et al., 1992, Brockelbank and Tam, 1991, Chen et al., 1988, Cooper et al., 1987, Day and Mueller, 1988, 1989, Fukushima, 1988, Heipke and Kornus, 1991, Kaufman and Wood, 1987, Ley, 1988, Lo and Mulder, 1992, Otto and Chau, 1989, Renouard, 1992, Rosenholm, 1988, Shibasaki and Murai, 1988, Vincent et al., 1988. Major problems, affecting all previously developed algorithms, are the large radiometric differences between images acquired at different times, and the nonperspective SPOT image geometry. Stereoscopic images from SPOT have, in the best case, a time difference of 3 days. In practice, image pairs that are appropriate, i.e. have small cloud coverage, large base to height (B/H) ratio and large overlap, have a much larger acquisition time difference. SPOT has a linear CCD sensor with 6000 pixels. 6000 consecutive lines form one SPOT image. Thus, the perspective geometry is valid only in CCD line, but not in flight, direction. Matching algorithms that use epipolar images can not be applied in this case, because for epipolar transformation of SPOT images a DTM is required (Otto, 1988). Algorithms that use geometric constraints in order to match along the epipolar lines (without epipolar transformation of the images) can not be applied for the same reason. Thus, all matching algorithms perform a 2-D search, which, given also the problems of radiometric differences, clouds etc., leads to a large amount of errors.

The motivation behind this research was the aim to improve matching of SPOT images by integration of the sensor geometry and the treatment of radiometric differences. As far as the authors know, none of the published matching methods explicitly exploits the SPOT geometry to restrict the search space. At our Institute, we have for many years used geometric constraints in our matching algorithm in order to reduce the search space to 1-D. This approach has been successfully applied to frame imagery (aerial images, and CCD images of close-range applications). Our aim was to use a specific SPOT sensor model developed by Kratky in order to derive quasi epipolar lines and thus, apply geometric constraints even in the case of SPOT images. The details of our approach are explained in section 2.

Attempts to circumvent the problem of radiometric differences have concentrated on using images acquired within a short time interval. However, this is difficult to achieve and does not solve the problem. The along-track stereo, which is provided by current and future systems like the JERS-1, MOMS-02, SPOT 5, will strongly reduce these problems but can not eliminate them due to different perspective views, clouds and occlusions. Fusion and matching of multitemporal and multi-
sensor data, as in change detection applications, will retain their importance even in the era of along-track stereo. Thus, the authors decided to attack this problem, which has been up to now treated only to a limited extent. The idea is to use gradient magnitude images, thus eliminating radiometric differences in areas of low texture. Preliminary investigations have shown that the majority of the edges remain stable. However, different edges exist due to clouds, shadows, different perspective views, new edges within fields due to agricultural activities, human intervention, water level, snow coverage, changes in the tree canopies etc. (Figure 1). A method should be developed to try to detect the different edges.

A third aspect of our research was the development of algorithms for the automatic detection of blunders. Existing matching algorithms may supply results relatively fast, but since the amount and size of errors are considerable, a time-consuming and cumbersome manual editing is required before deriving high quality DTMs.

![Figure 1. Radiometric differences due to agricultural activities (left pair) and due to clouds and shadows (right pair).]

### 2. TEST DATA AND SPOT GEOMETRIC MODEL

A stereo SPOT panchromatic level 1A model over W. Switzerland was acquired. The inclination of the sensor’s optical axis was 23.4° R and 19.2° L respectively, leading to a B/H ratio of ca. 0.8. The acquisition dates were 20.7.1988 and 27.8.1988 with significant radiometric differences between the two images, particularly in agricultural areas. Figure 1 shows some typical image parts with large radiometric differences. The elevation range was 350 - 3000 m. The following preprocessing was applied to the original digital images:

- reduction of periodic and chess pattern noise
- Wallis filtering ([Wallis, 1976](#)) for an adaptive nonlinear local contrast enhancement

As previously explained, a SPOT image consists of 6000 consecutive lines. Each line has its own exterior orientation parameters (position and 3 attitude angles) but, due to the smooth trajectory of the satellite, these parameters are highly correlated. Thus, the exterior orientation parameters that are estimated by most SPOT sensor models are the 6 parameters for the center line of the image plus change rates of these parameters from line to line. [Kratky, 1989b](#) has developed a strict mathematical model with (a) linear and quadratic rates of the sensor position computed from rigorous elliptical orbital equations, (b) linear and optionally quadratic rates for the attitude angles, and (c) additional parameters for the camera constant and the principal point. 136 control and check points were used with Kratky’s model. 10 of the points were used as control points with a linear model of the attitude rates of change. The pixel coordinates were measured in one image manually and transferred to the second one by template matching, and their object coordinates were digitised from 1:25,000 topographic maps. The RMS error of the check points was 9 - 10 m in planimetry and 6 m in height.

[Kratky, 1989a](#) also provides direct projection equations from one space to another (two image spaces, object space) by means of polynomial mapping functions (PMFs). The PMFs consist of 3rd - 4th degree polynomials with 11 - 16 terms, whereby the object space is reduced to two dimensions by extracting the elevation, i.e. the elevation Z is an independent parameter connecting all three 2-D spaces. The polynomial coefficients are estimated by least squares adjustment after the sensor orientation is estimated by the strict model. The PMFs are much faster and almost equally accurate as rigorous transformations using the strict model. Our aim was to try to use the PMFs in order to define quasi epipolar lines. When the ray of an imaged point is projected by using the PMFs onto the other image of a stereo pair (epipolar line) it is with a very good approximation a straight line. If a straight line is defined by the projection of a small ray segment which is centred at the correct point position in object space $P_o$ (see Figure 2), then the deviation of the epipolar line from the straight line would be 0.25 pixel for a height error of more than 7 km. Thus, the aforementioned straight line can be used as a quasi epipolar line. More details on the characteristics of the PMFs can be found in [Baltsavias and Stallmann, 1992a](#).

An overview of the different stages of our matching method is given in Figure 3. Details of each stage are given in sections 2 to 6.
3. MODIFIED MPGC

MPGC is described in detail in Baltsavias, 1991. It is an extension of least squares matching (LSM). LSM fits a grey level patch in one image to a selected patch in a reference (template) image by means of an affine geometric transformation and two radiometric corrections, within a least squares based estimation. LSM is an area-based matching approach, based on the assumption that the surface consists of small planar facets. MPGC combines LSM and geometric constraints which are derived from a priori known information and formulated either in image or object space. The constraints that are usually implemented are based on the collinearity equations; other constraints of relevance to machine vision, and particularly to precise edge measurement and tracking, are published in Gruen and Stallmann, 1992. The constraints lead to a 1-D search space along a line, thus to an increase of success rate, accuracy and especially reliability, and permit a simultaneous determination of pixel and object coordinates. Any number of images (more than two) can be used simultaneously. The measurement points are selected along edges that are nearly perpendicular to the geometric constraints line. The approximations are derived by means of an image pyramid. The achieved accuracy is in the subpixel range. The algorithm provides criteria for the detection of observation errors (i.e. erroneous grey levels) and blunders, and adaptation of the matching parameters to the image and scene content.

In the case of matching of SPOT images the geometric constraints were formulated as follows. First, given a measurement point in one of the images (template image) a height approximation is needed. If the existing approximations refer to the pixel coordinates, then the height is computed by using the pixel coordinates in the reference image, the x pixel coordinate in the second image and the image to image PMFs. This height Z is altered by a height error \( \Delta Z \). Using the heights \( Z + \Delta Z, Z - \Delta Z \), the pixel coordinates in the template image are projected by the image to image PMFs in the second image where they define the geometric constraints line (see Figure 2). In the sequel, this quasi epipolar line will be referred to as epipolar line. The centre of the patch of the second image which is used for matching is forced to move along this line by means of a weighted observation equation of the form

\[
v_c = (x + \Delta x) \cos \beta + (y + \Delta y) \sin \beta - p ; \quad P_c \quad \text{... weight coefficient matrix}
\]

where \((x, y)\) the approximate pixel coordinates of the corresponding point in the second image, \((\Delta x, \Delta y)\) the unknown x- and y-shift, and \(v_c\) the residual error.

Equation 1 is equivalent to the distance of a point \((x + \Delta x, y + \Delta y)\) (the patch centre of the second image) from a straight line. The epipolar line is expressed by the normal equation of a straight line, where \(p\) is the distance of the line from the origin and \(\beta\) is the angle between the perpendicular to the line and the x-axis.
Figure 3. Flow chart of the different processes for the generation of DTM from SPOT images.

1 Optional, not used in this test.
If the patch of the second image does not lie on this line, then it jumps onto the line right in the first iteration. With our data, the epipolar lines are approximately horizontal, i.e. any error in the y-direction will be eliminated right in the first iteration. Since the epipolar lines are horizontal, the measurement points must be selected along edges that are nearly vertical in order to ensure determinability and high accuracy. Some advantages of the geometric constraints will now be presented. SPOT images include due their small scale a high degree of texture, i.e. edges. Measurement points lying along edges nearly vertical to the epipolar line can not be safely determined with other matching techniques, but with our approach they can as they lie at the intersection of two nearly perpendicular lines. Figure 3 illustrates such an example. Another usual problematic case is that of multiple solutions. With geometric constraints side minima can only result if they fall along the epipolar line. Figure 5 shows an example with and without geometric constraints.

**Figure 4.** Matching along edges without (left) and with (right) constraints. The epipolar line is the white line in the right image. The black frame is the initial position and the white frame with the black centre cross the final position.

**Figure 5.** Multiple solution matching without (left) and with (right) constraints.

### 4. DATA PREPROCESSING AND SELECTION OF MEASUREMENT POINTS

First, the gradient magnitude images are computed. To reduce weak edges due to noise, which is very noticeable in SPOT images, all gradients with a magnitude less than a threshold $T$ are set equal to $T$. The threshold is selected as a function of the mean and the standard deviation of the gradient magnitude image (in this case $T = \text{mean} - \text{standard deviation}$). The same function should be used for both images to ensure equal treatment. The threshold should not be too high otherwise (a) useful texture is deleted, and (b) the edges are broken and significant differences between the two images occur due to different edge strength. This approach eliminates noise but also low texture which is however not very likely to lead to accurate matching results. An example is shown in Figure 6.

As already mentioned, the measurement points are selected along edges nearly perpendicular to the epipolar lines. In order not to reduce the number of the selected points too much (and thus their density, which influences the DTM accuracy), points along edges with an angle of $\pm 45^\circ$ with the perpendicular to the epipolar line should also be selected. To avoid clustering of good points a thin-out window for non-maxima suppression is defined. To reduce the selection of points lying at small
and faint noisy edges the points are extracted in the first level of the image pyramid. Our approach is to match the same number of points in all pyramid levels. Thus, a selected point must have the aforementioned properties in all pyramid levels. Generally, the approach to be followed is to detect good points in all levels of the image pyramid of the template image and keep the points that appear in all pyramid levels. However, these SPOT images had a lot of texture and this was expressed in all pyramid levels. By going up in the image pyramid, the relative number of selected points was actually increasing.

![Image 1](image1.png)  ![Image 2](image2.png)  ![Image 3](image3.png)

**Figure 6.** Grey level image (left), gradient magnitude image (middle), thresholded gradient magnitude image (right)

To avoid selecting points at regions of radiometric differences, especially ones with a large area extent (like clouds), the following approach is used. Using the PMFs and an average height of the scene (derived either from a priori knowledge or from the average height of the control points used in the rigorous SPOT model), or a polynomial transformation derived from the pixel coordinates of the control points, the search image is registered with the template image. If the registration were perfect, a simple subtraction of the two images would give us the different edges. Since the registration is not perfect, an image pyramid is created so that at the highest level the misregistration error is within pixel range.

![Image 4](image4.png)  ![Image 5](image5.png)  ![Image 6](image6.png)

**Figure 7.** Top row: left (left) and right (middle) SPOT image at 4th pyramid level and normalized difference image (right). Bottom row: binarized difference image (left), image with selected points (middle), image with cleaned selected points (right)
Then through subtraction, the different edges are detected by binarising the difference image with an absolute threshold. This binary image can possibly be dilated in order to avoid selecting points whose patch would partially fall inside areas with radiometric differences. These disturbance areas are projected in all pyramid levels and convolved with the selected points in order to clean the selected points. An example is shown in Figure 7. With this method small radiometric differences cannot be detected.

5. DERIVATION OF APPROXIMATIONS

After the PMFs are computed an average height is used in order to determine the position of the selected points in the search image. To check the quality of these approximations the 136 points were projected onto the search image by using an average height of 1000 m, and these pixel coordinates were compared to the known ones. The RMS differences were 32 pixels in x and 2 pixels in y, with the maximum error being 72 and 5 pixels respectively. Thus, a refinement of these approximations by an image pyramid approach is necessary. An alternative approach would be to actually transform and resample the search image by using the PMFs and the average height. In this case, the disadvantages are (i) the computational costs for the transformation and the resampling, and (ii) the degradation of the data. The advantages include: (i) matching can be performed using only shifts, thus resulting in computational gains which in case of many points exceed the loses, (ii) detection of radiometric differences can be applied as proposed above, and (iii) since the y-parallax of the co-registered images is very small, the images can be viewed stereoscopically (which is anyway required in digital photogrammetric workstations).

6. ACCURACY TESTS AND BLUNDER DETECTION

The accuracy of the matching algorithm was tested by using the 25 m DTM of Switzerland which is generated by the Federal Office of Topography. The DTMs of the 1:25000 map sheets 1224 and 1225 were acquired. Each DTM has 701 x 481 nodes in E-W and N-S direction respectively. The 1224 DTM has an accuracy (RMS) of 1.9 m. The height range is 900 m but the terrain is generally smoothly changing (average slope 7°). The 1225 DTM has an accuracy of 4.1 m and a height range of 1500 m. Although it is not the most extreme case that can be encountered in Switzerland, the terrain is in most parts steep (average slope 18°). Forests cover ca. 20% of map sheet 1224 and 35 - 40% of map sheet 1225. In the latter there are also lakes covering ca. 4% of the area. Some clouds were present. The radiometric differences were larger in map sheet 1224 which included agricultural areas.

For matching, the following 5 different versions were compared:

- Version 1: no geometric constraints, conformal transformation
- Version 2: constraints, conformal transformation
- Version 3: constraints, shifts only
- Version 4: constraints, conformal transformation, grey level images
- Version 5: constraints, two shifts and one rotation

All versions used a patch size of 17 x 17 pixels and gradient magnitude images with the exception of version 4 that used grey level images. The aim was to compare constraints vs. no constraints, grey level vs. gradient magnitude images, conformal vs. shifts and rotation vs. shift transformation. The approximations for the parallaxes were derived by a hierarchical approach using image pyramids, 6 pyramid levels, including the original image were used. They were created with a decimation factor of 2 and a 3x3 Gaussian low-pass filter. The same points were matched in all pyramid levels.

The results of matching were analysed for automatic detection of blunders. The criteria that have been used for quality analysis are: standard deviation of unit weight from the least square matching, correlation coefficient between the template and the patch, number of iterations, x-shift (i.e. change from the approximate values), standard deviation of y-shift, y-shift, standard deviation of y-shift, and the size of the used shaping parameters (shaping parameters = x-, y-scales and shears). After matching, the median ($M$) and the standard deviation of the mean absolute difference from the median ($s(MAD)$) were computed for each criterion. The median and the $s(MAD)$ were used instead of the average and the standard deviation because they are robust against blunders. For each criterion, the threshold for the rejection of a point was defined as $M + N \cdot s(MAD)$. N was selected to be 3 for all criteria with the exception of the number of iterations, the two shifts and the scale which should be left to vary more ($N = 4$). A point was rejected (i) when one of its criterion did not fulfil the aforementioned threshold (relative threshold derived from the image statistics), or (ii) one of its criteria did not fulfil a very loosely set threshold, e.g. for the correlation coefficient 0.2 (absolute threshold, valid for all images). The same N and absolute thresholds were used for all versions. This blunder detection scheme was successfully applied in an old test with very good approximate values. In the current test some problems occurred. The number of the remaining points in the 0th level was significant decreased when the blunder detection test was applied after each pyramid level. Thus, we decided to apply the test only to the results of the 0th level. However, wrong points in the upper pyramid levels were diverging from their correct po-
position as matching sequentially proceeded down the image pyramid. These points were typically fitted to a side-minimum and thus were not detected by the blunder detection test. Since they were far away from their correct position, their height was grossly erroneous, sometimes by several hundred meters. In this case the problem to be solved is to exclude blunders, from arbitrarily, and partly not densely, distributed points.

To achieve this we developed an algorithm that uses robust statistics of the heights (based again on median and $s(MAD)$) within 3 neighbourhoods centred at each point to be examined, whereby a minimum number of points within each neighbourhood is required to ensure a safe estimation of the statistics. The size of the neighbourhood and the minimum number of neighbours, which is proportional to the former, are decreased when the height gradient magnitude increases, i.e. the terrain becomes steeper. Points that do not fit to their neighbourhood were replaced by their neighbourhood median. The aim of this adaptive local nonlinear filtering was to reject the blunders, without smoothing the terrain, and propagating the blunders as if the case with low-pass filtering. Points with very few neighbours were rejected, although they may be critical for a complete surface description and correct DTM interpolation. Although the algorithm needs further development and testing, it performs well, particularly when the point density is sufficient. Table 1 gives information on the amount of rejected points.

As it can be seen from Table 1, the amount of successfully matched points decreases and the percentage of detected blunders increases when (i) no geometric constraints are used (version 1), and (ii) grey level images are used (version 4). From the remaining versions, the one using shifts results in more successful points because it is more stable (robust) than versions 2 and 5 which use a scale/rotation and a rotation respectively and because less criteria are used for the first blunder detection method.

For the accuracy analysis two comparisons were made:

- The matched points are bilinearly interpolated in the reference DTM grid and the differences between the interpolated heights and the heights as estimated by matching are computed (Tables 2 and 3).
- A new DTM was derived from the matched points and compared to the reference DTM.

Table 2 gives an accuracy estimate of the raw results of the 0th pyramid level. These results permit a comparison of the matching accuracy of the five versions. Version 2 and 5 perform similarly with the latter being slightly more accurate. Version 3 is worse, and version 1 and 4 are the less accurate.

Table 3 shows the final results after blunder removal. From a comparison of Tables 2 and 3 it is clearly visible that the two methods for blunder detection lead to an immense improvement of all accuracy indicators. Automatic quality control is indispensable and can take over the job of tedious and time-consuming manual editing. The maximum absolute error, the RMSE, and the percentage of errors over 40 m of Table 2 have been improved on the average by a factor 1.4, 2.1 and 3.2 respectively after using the first blunder detection method. The latter results have been further improved by a factor 6.2, 3.2 and 2.5 after using the second blunder detection method. The second blunder detection is particularly attractive, since it rejects 3 - 7 times less points than method I. The points rejected by method I as well as the unsuccessful points (the ones that needed more than 20 iterations) include many wrongly rejected good points. This deficiency can be removed and a cooperation between the different blunder detection procedures is planned. The percentage of errors greater than 40 m is generally less than 2%. Large errors occur especially in three types of areas: (a) at the mountain-ridges and cliffs, (b) at forest areas, and (c) on the surface of lakes. The RMSE is in the 10 m level and compares very favourably with the 6 m RMS in Z of the 126 manually selected and matched check points. The mean difference is small, indicating absence of large systematic errors.

<table>
<thead>
<tr>
<th>Version</th>
<th>Map sheet 1224</th>
<th>Map sheet 1225</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Method I</td>
<td>Method II</td>
</tr>
<tr>
<td>1</td>
<td>21.2%</td>
<td>7.1%</td>
</tr>
<tr>
<td>2</td>
<td>16.7%</td>
<td>5.9%</td>
</tr>
<tr>
<td>3</td>
<td>13.4%</td>
<td>4.3%</td>
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<tr>
<td>4</td>
<td>19.4%</td>
<td>6.8%</td>
</tr>
<tr>
<td>5</td>
<td>15.8%</td>
<td>4.9%</td>
</tr>
</tbody>
</table>

As it can be seen from Table 1, the amount of successfully matched points decreases and the percentage of detected blunders increases when (i) no geometric constraints are used (version 1), and (ii) grey level images are used (version 4). From the remaining versions, the one using shifts results in more successful points because it is more stable (robust) than versions 2 and 5 which use a scale/rotation and a rotation respectively and because less criteria are used for the first blunder detection method.
Version 1 (without constraints) is surprisingly good. This is mainly due to the fact that these results are based on fewer points due to many detected blunders (Table 1) by the blunder detection scheme. However, less points lead to a less accurate interpolated DTM especially in mountainous terrain. Another reason is due to the choice of points along nearly vertical edges. Thus, the precision in x-direction is good and errors in y (gliding along the edge) influence minimally the estimated heights due to the horizontal base. Version 4 has similar accuracy as the version with gradient magnitude images (version 2). The difference is not so big again due to many detected blunders for version 4. The shift version (version 3) performed, as expected, worse than versions 2 and 5. Version 5 was expected to perform slightly better than version 2, because with the latter the scale is not always well-determinable. However, the viewing angles and the steep terrain, particularly in map sheet 1225, makes the use of a scale necessary for a better geometric fit of the patch to the template. Our interpretation of Table 3 is that although versions 1 and 4 seem to perform very well, they lead to a less accurate DTM interpolation in rugged terrain because they lead to less points.

### Table 2 Differences of estimated heights (raw data) to reference DTM (in meters)

| Version | Map sheet 1224 | | | Map sheet 1225 | | |
|---------|----------------|------|------|----------------|------|
|         | max. absolute | RMSE | mean | % ≥ 40 m | max. absolute | RMSE | mean | % ≥ 40 m |
| 1       | 1260          | 75.5 | +2.7 | 10.9      | 1944          | 94.4 | -3.3 | 9.0     |
| 2       | 1917          | 62.9 | +1.5 | 9.1       | 1973          | 88.5 | -0.2 | 7.3     |
| 3       | 1931          | 68.3 | +2.7 | 8.4       | 2074          | 97.9 | 0.0  | 8.8     |
| 4       | 1854          | 63.9 | +6.3 | 11.7      | 2845          | 132.9| +16.2| 8.4     |
| 5       | 1566          | 65.8 | +2.8 | 8.2       | 1339          | 78.1 | -1.1 | 8.1     |

### Table 3 Differences of estimated heights to reference DTM after 2st blunder detection method (in meters)

| Version | Map sheet 1224 | | | Map sheet 1225 | | |
|---------|----------------|------|------|----------------|------|
|         | max. absolute | RMSE | mean | % ≥ 40 m | max. absolute | RMSE | mean | % ≥ 40 m |
| 1       | 76            | 7.9  | +1.6 | 0.3        | 225           | 11.2 | -1.0 | 1.1     |
| 2       | 78            | 9.3  | +2.5 | 0.3        | 218           | 13.6 | -0.4 | 1.5     |
| 3       | 428           | 14.7 | +3.0 | 0.7        | 401           | 17.3 | -1.0 | 2.8     |
| 4       | 131           | 10.5 | +3.0 | 0.6        | 294           | 12.7 | +0.9 | 1.4     |
| 5       | 82            | 9.6  | +2.5 | 0.5        | 198           | 14.9 | -0.9 | 2.0     |

A new DTM was derived from the matched points and compared to the reference DTM. The results are worse than those of Table 3 due to interpolation errors (ca. 270000 points were interpolated from 10000 - 16000 points). Still the results for map sheet 1224 are close to 10 m. The results for map sheet 1225 are 30 - 40 m due to mountainous terrain, many forests and the lake. With denser measurement points they should be close to the results of map sheet 1224. The results of versions 1 and 4 are worse than those of the other versions in the rugged terrain of map sheet 1225 since their results are less dense.

### 7. CONCLUSIONS

A matching algorithm for SPOT images was presented that uses a photogrammetric sensor model to impose constraints that reduce the search space from 2-D to 1-D. The algorithm severely reduces the problems caused by radiometric differences, and
determines in one step pixel and object coordinates. The use of gradient magnitude images instead of grey level images improves the results. A conformal, a rotation/shift or a shift transformation, the latter however with smaller patch size, may lead to similar results.

Problematic cases like multiple solutions, radiometric differences and occlusions are reduced and the computation time decreases due to the 1-D search. A blunder detection scheme is proposed that uses criteria derived mainly from the statistics of the results. It leads to an impressive improvement of all accuracy indicators. In particular, it reduces the percentage of errors larger than 40 m to 0.5 - 2%. A deficiency of our test was the rejection of too many points, out of which many were correct, with obvious negative influence on the DTM interpolation.

The accuracy of the matching is in the 10 m range. For the interpolated DTM it clearly depends on the density of measurement points and for sufficient density it can be in the 10 - 20 m range. Regions with low point density due to radiometric differences, low texture or shadows must be filled-in with manually measured points before the DTM interpolation.

8. ACKNOWLEDGEMENTS

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9. REFERENCES


