APERS : Affine Parameters Estimation by Random Sampling

A robust tie-points detection algorithm

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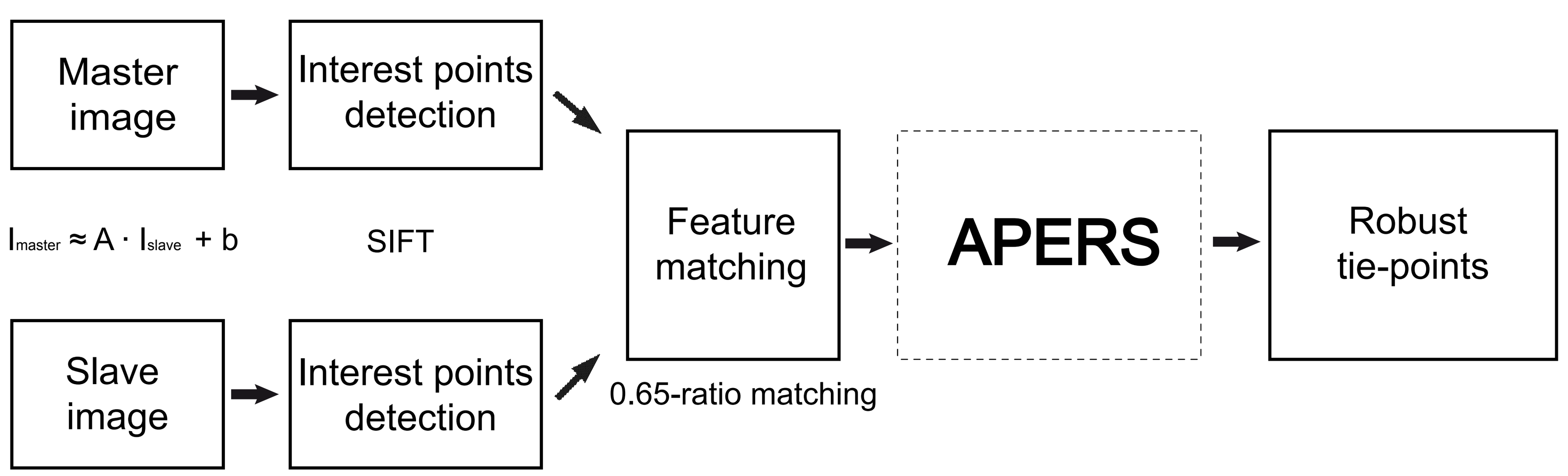
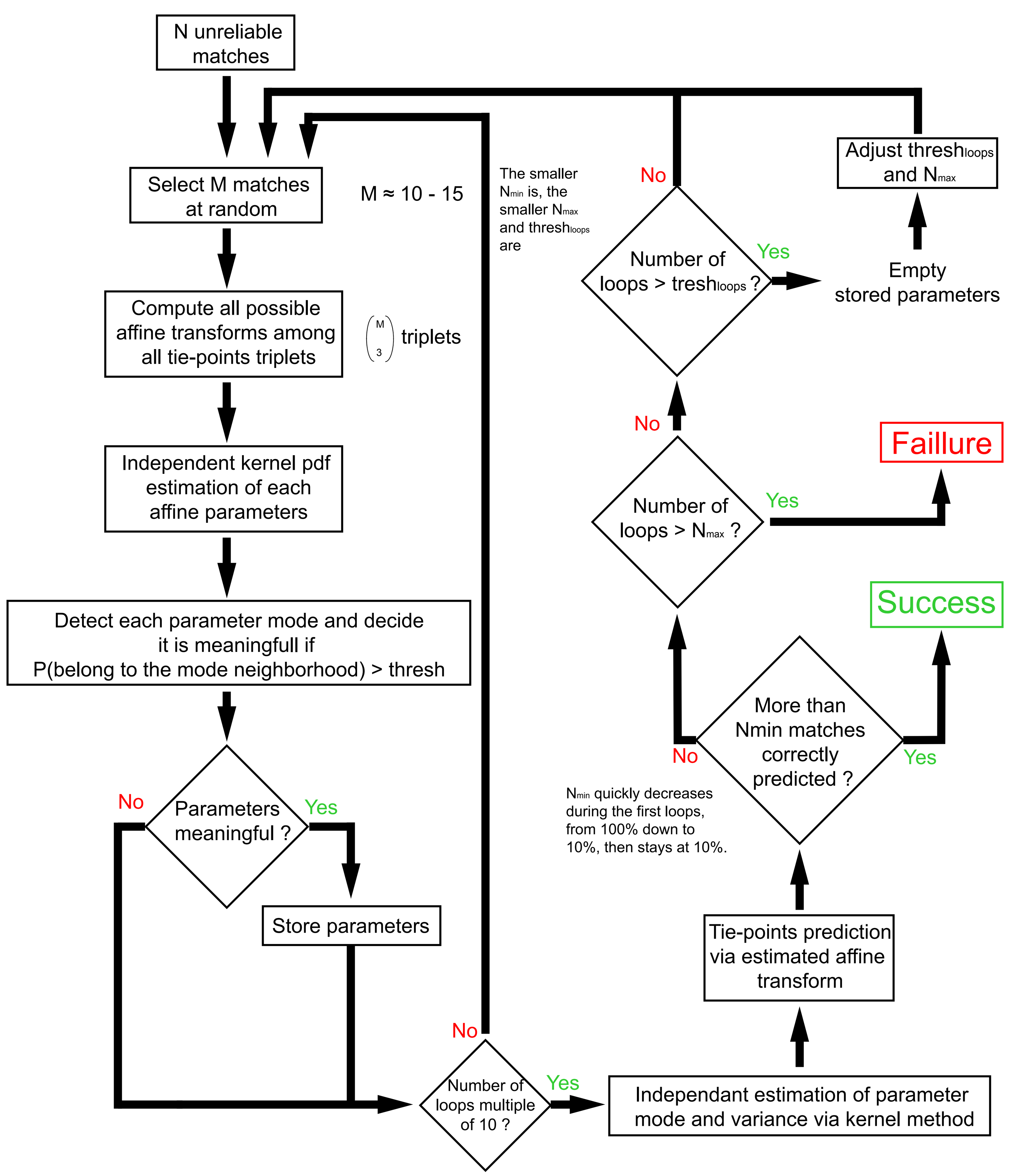
The COSI-Corr software [2] needs a set of not necessarily very accurate, but robust tie-points to initiate its calculations. There are many algorithms that automatically extract features from images, but all the matching techniques are made for very similar scenes. We developed an algorithm that decides, given a set of matches between two images, which matches follow the same affine model, even when drastic changes happened between the scenes and when the proportion of mismatches is very important. The Affine Parameters Estimation by Random Sampling (APERS) assumes that the two images are approximately mapped by an affine transform. We use here the matches given by Lowe's famous SIFT [1] method, and we are able to automatically detect correct matches up to a proportion of 90% of outliers, while accepting rigorously no outliers. Any other set of matches can be used as entry of the algorithm, and it would be simple to extend it to a more complicated transform model (e.g. homography) as the computation time is linear in the dimension of the estimated mapping. The largest improvement compared to similar algorithms such as ORSA [3] is that outliers are never accepted, even when the proportion of mismatches is huge.

Complete image matching procedure

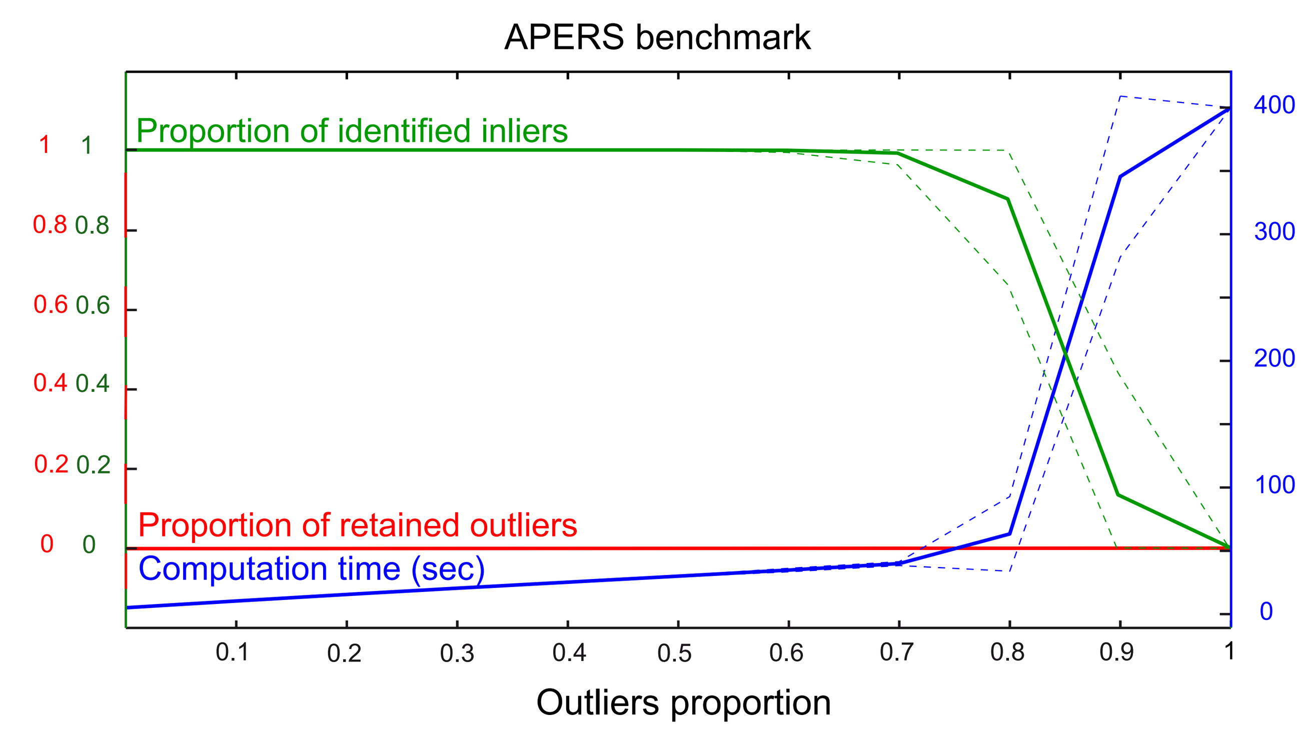


APERS flowchart



Theoretical results

APERS benchmark



Performances of APERS for different proportion of outliers. Each experiment consists in generating 512 slave points randomly, following a uniform distribution in a 1024x1024 pixel square. We then randomly create an affine transform and compute the 512 images of the 512 slave points. We then change a proportion of the matches, reassigning them randomly in order to simulate mismatches. We finally add a one pixel standard deviation gaussian noise to all matches. We proceeded to 11 sets of 50 experiments, each set corresponds to a different proportion of outliers.

The full curves represent the performances of the algorithm, averaged over 50 experiments. Note than every outlier was systematically filtered.

Expected variance calculation

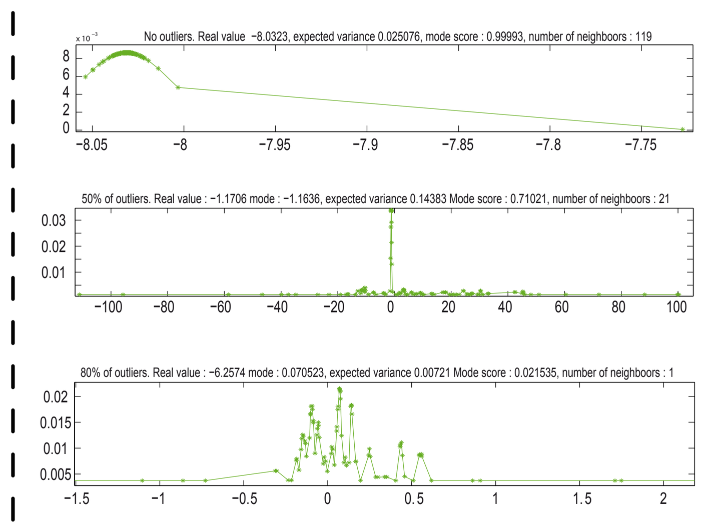
We write :

$$A \cdot \begin{pmatrix} x_1^s & x_2^s & x_3^s \\ y_1^s & y_2^s & y_3^s \\ 1 & 1 & 1 \end{pmatrix} = \begin{pmatrix} \overline{x_1^m} + x_1^m & \overline{x_2^m} + x_2^m & \overline{x_3^m} + x_3^m \\ \overline{y_1^m} + y_1^m & \overline{y_2^m} + y_2^m & \overline{y_3^m} + y_3^m \\ 1 & 1 & 1 \end{pmatrix}$$

and $A = \begin{pmatrix} a & c & t_x \\ b & d & t_y \\ 0 & 0 & 1 \end{pmatrix}$ where the dashed elements represent noise and tilted elements are approximation due to the noise. If we consider the noise follows a gaussian distribution, we can estimate the probability density of every coefficient of the affine transform matrix, e.g.

$\tilde{a} \sim N(\tilde{a}, \frac{\tilde{a}}{x_1^m})$. Inside an experiment, for every coefficient, we use the average variance of all triplets for the kernel method, then we replace the coefficient value by the mode of the produced distribution to re-estimate the variance.

The kernel method



Zoom on the result of the kernel method applied to a 10-match experiment (120 triplets). The three figures correspond to different proportion of outliers (top to bottom, 0%, 50% and 80% of outliers).

These figures represent how the difficulty to estimate a coefficient rises with proportion of outliers. The more there are outliers, the wider the points are spread compared to the expected variance. It leads to a reduction of the «mode score», witch is the empirical probability for one of the 120 points to be three times the variance away from the mode, and make us able to detect if an experiment is meaningful or not.

The "number of neighbours" shows how many points are inside that interval. We systematically discard experiment with strictly less than 4 neighbours, as one meaningful experiment must include at least 4 good matches that will give 4 triplets with similar result.

References:

[1] D. G. Lowe. "Distinctive image features from scale-invariant keypoints". Int. J. Comput. Vision, 60(2) :91–110, 2004.

[2] S. Leprince, S. Barbot, F. Ayoub and J. P. Avouac, "Automatic and Precise Ortho-rectification, Coregistration, and Subpixel Correlation of Satellite Images, Application to Ground Deformation Measurements", IEEE Transactions on Geoscience and Remote Sensing, Vol.45, No.6, June 2007.

[3] L. Moisan and B. Stival. "A probabilistic criterion to detect rigid point matches between two images and estimate the fundamental matrix". International Journal of Computer Vision, 57(3) :201–218, 2004.

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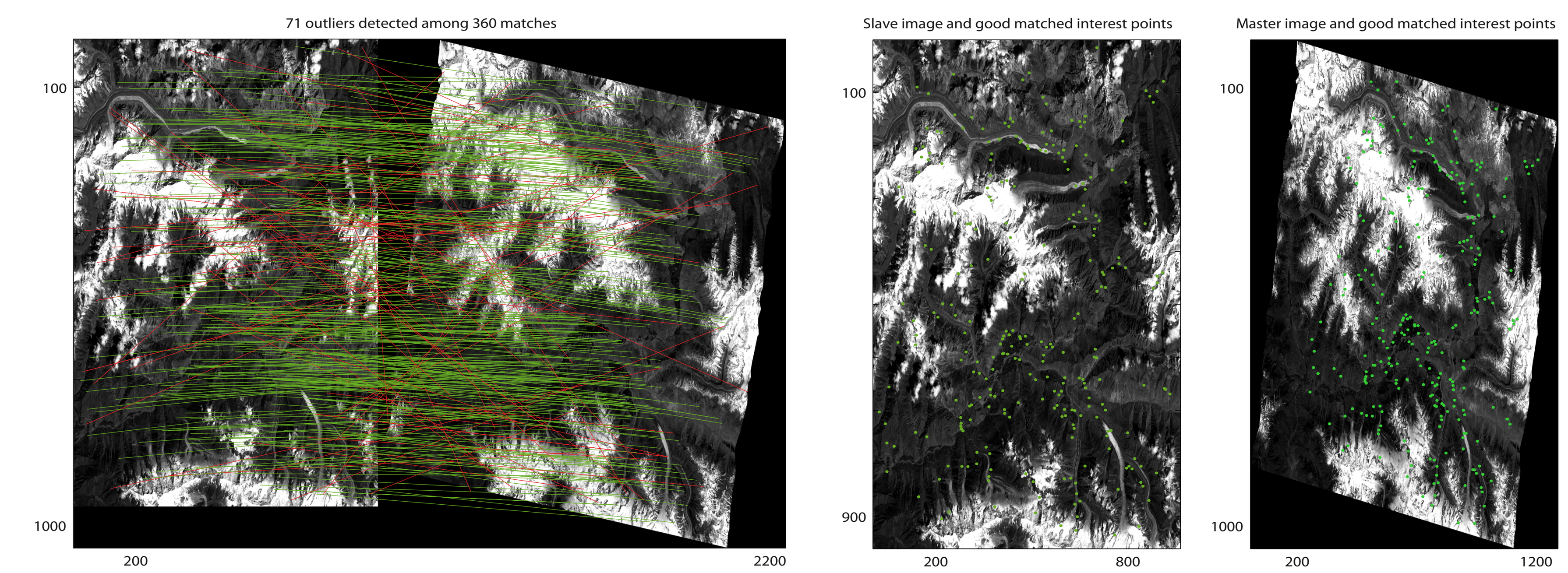
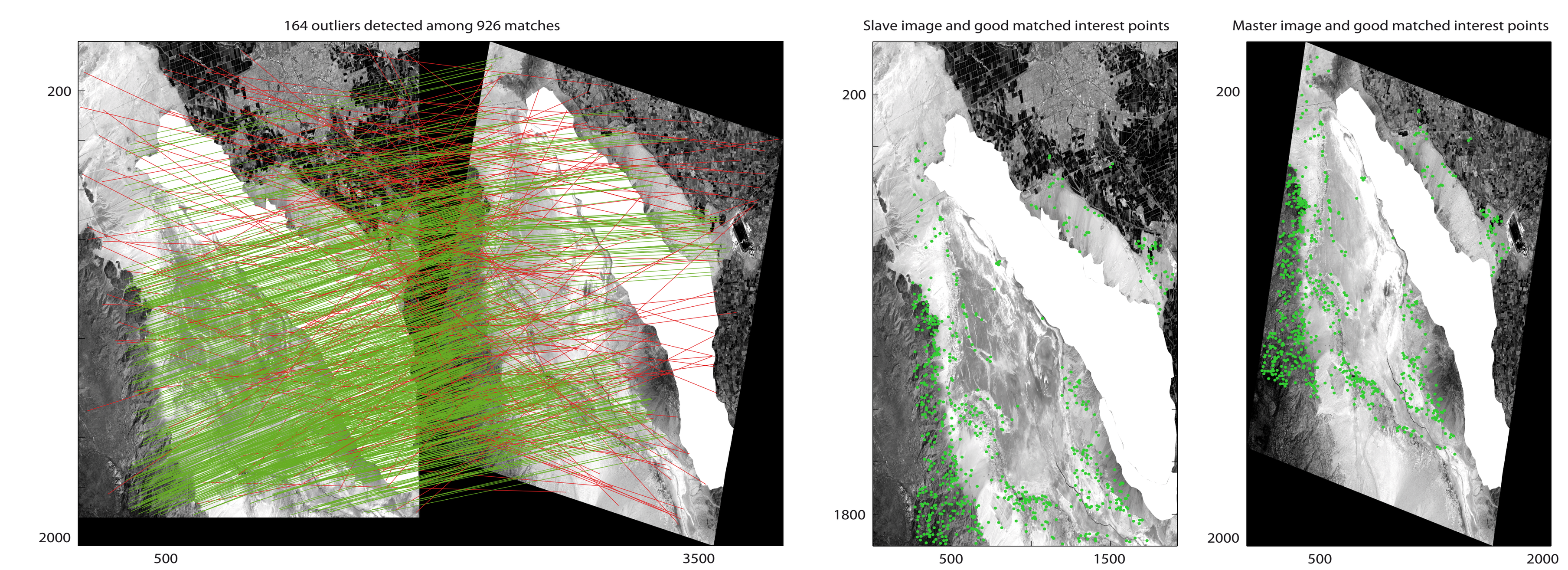
Application to remote sensing imagery

Pakistan glacier, SPOT 4 10m sub-sampled at 12%.
From left to right : The slave and master images with good (green) and bad (red) matches, Slave image and good matches location, Master image and good matches location.

360 matches, 71 outliers (20 %), 289 inliers (80%)

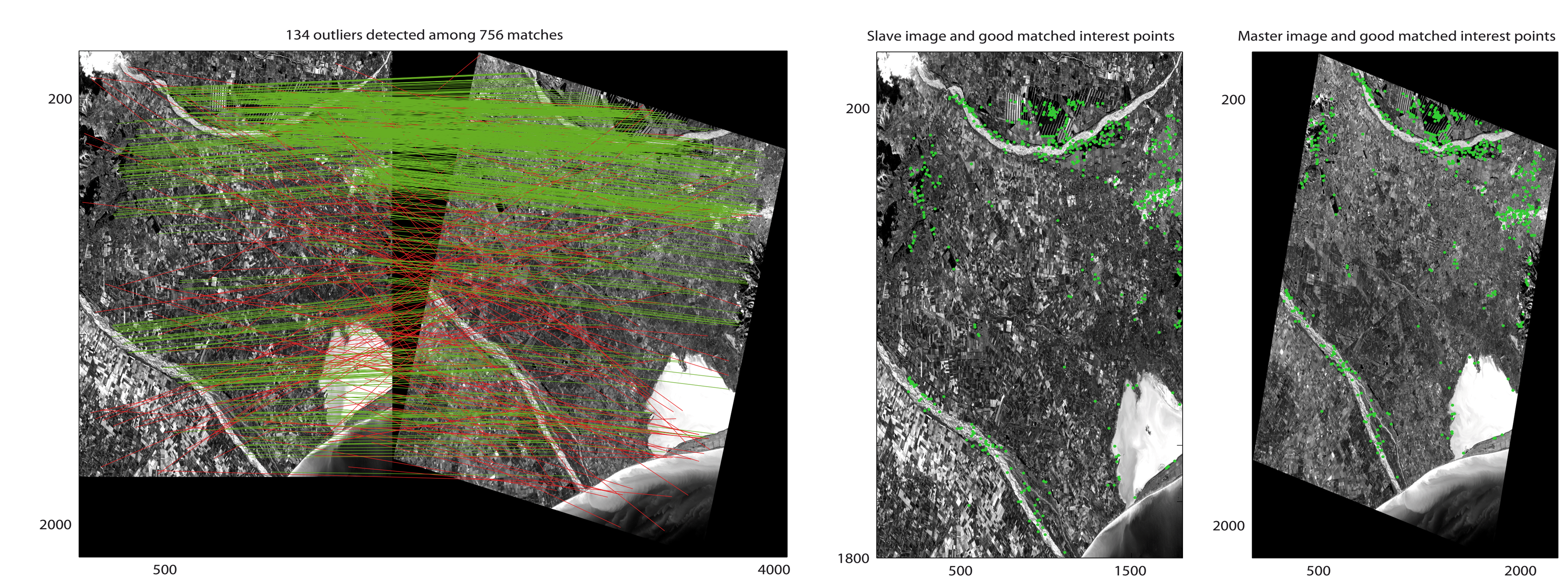


El Mayor area with white mask on the assumed fault location to avoid matches that would distort COSI-Corr calculations, SPOT 5 2.5m subsampled at 7%.
From left to right : The slave and master images with good (green) and bad (red) matches, Slave image and good matches location, Master image and good matches location.



Darfield, New Zealand SPOT 4 10m subsampled at 30%.
From left to right : The slave and master images with good (green) and bad (red) matches, Slave image and good matches location, Master image and good matches location.

756 matches, 134 outliers (18%), 622 inliers (82%)



San Andreas fault, California, USA shaded LIDAR DEM 50cm, aerial photo 1m both downsampled at 12%.
From left to right : The slave and master images with good (green) and bad (red) matches, Slave image and good matches location, Master image and good matches location.

130 matches, 36 outliers (28%), 94 inliers (72%)