In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents | Author Index | Keyword Index

AUTOMATIC REGISTRATION OF AIR-BORNE AND SPACE-BORNE IMAGES BY TOPOLOGY MAP-MATCHING WITH SURF PROCESSOR ALGORITHM

Anna Brook, Eyal Ben-Dor

Remote Sensing Laboratory, Tel-Aviv University, Israel
anna.brook@gmail.com

Commission VI, WG VI/4

KEY WORDS: Automatic registration, Multi-sensors airborne and space-borne fusion, Change detection, Weight-based topological map-matching algorithm (tMM), Scaling and image rotation

ABSTRACT:

Image registration is widely used in many Remote Sensing applications. The existing automatic image registration techniques fall into two categories: the intensity-based and the feature-based methods, while the feature-based technique (which extracts structures from both images) is more suitable for multi-sensors fusion, temporal change detection and image mosaicking. Conventional image registration algorithms have greatly suffered from quantity and spatial distribution of extracted control points. In this study, we propose a novel method for automatic image registration based on topology rules (AIRTop) for temporal change detection and multi-sensors (airborne and space-borne) fusion. In this algorithm, we first apply the SURF (Speeded Up Robust Features) method to extract the landmarks structures (roads and buildings) of the given images, and then they are expressed by a topology rules, which define the permissible spatial relationships between features. The defined rules for a weight-based topological map-matching algorithm (tMM) manage the relationships between features in different feature classes (roads and buildings) and present a robust method to find a control points in both reference and sensed images. The main focus in this study is on scale and image rotation invariant the quality of the scanning system. These seem to offer a good compromise between feature complexity and robustness to commonly occurring deformations. The skew and the anisotropic scaling are assumed to be second-order effects that are covered to some degree by the overall robustness of the sensor. Experimental results show that our method can provide better accuracy than the conventional registration process.

1. INTRODUCTION

Image registration is a critical preprocessing procedure in all remote sensing applications that utilize multiple image inputs, including multi-sensor image fusion, temporal change detection, and image mosaicking. The recent interest in temporal change detection and modeling transform make the automatic image registration to important stage of preprocessing the data (Moigne et al., 2002). The automatic registration of images has generated extensive research interests in the fields of computer vision, medical imaging and remote sensing. Comprehensive reviews include Brown (1992) and Zitova and Flusser (2003).

The existing automatic image registration techniques fall into two categories: the intensity-based and the feature-based methods (Zitova and Flusser, 2003). The feature-based technique extracts salient structures from sensed and reference images by invariance and accuracy of the feature detector and by the overlap criterion. As the significant regions (e.g. roofs) and lines (e.g. roads) are expected to be stable in time at fixed position, the feature-based method is more suitable for multi-sensors fusion, temporal change detection and image mosaicking. The method generally consists of four steps (Jensen et al., 2004): 1) control points (CPs) extraction, 2) transformation model determination, 3) image transformation and re-sampling, and 4) registration accuracy assessment. Among the four steps, the first is the most complex, and its success essentially determines the registration accuracy. Thus, the detection method should be able to detect the same features in all projection and different radiometrical sensitivities regardless of the particular image / sensor deformation.

The search for discrete CPs can be divided into three main steps: 1. selection of "interesting points", 2. Description of nearest points or features, 3. matching between images. The most valuated property of CPs detection is its repeatability. The description of nearest points has to be distinctive but robust to noise, potential displacements as geometric and radiometric deformations. In order to succeed, the matching technique has to be accurate and sufficient while detection scheme has to simplify the above requirements.

This paper presents a novel method for automatic image registration based on topology rules (AIRTop) for temporal change detection and multi-sensors (airborne and space-borne) fusion.

2. AUTOMATIC IMAGE REGISTRATION

The AIRTop algorithm (Figure 1) consist four stages as any conventional registration method. First, the significant features extracted by applying SURF (Speeded Up Robust Features) method on both sensed and reference images and converted to vector format. The spatial distribution and relationship of these features expressed by topology rules and converts them to potential CPs by determine transformation model between sensed and reference images. The defined rules for a weight-based topological map-matching algorithm (tMM) manage, transform and re-sampling features of sensed image according to reference. Since AIRTop has a sufficient number of CPs the registration accuracy can be estimated with test point error (TPE) technique.

---

* Anna Brook, the Remote and GIS Sensing Laboratory, Tel-Aviv University. Ramat Aviv P.O. Box 39040 Tel Aviv 69978, Israel, Tel: 972-3-6407049 Fax: 972-3-6406243 Email: anna.brook@gmail.com.

In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents　　　　　　　　　　　Author Index　　　　　　　　　　　Keyword Index

2.1 Significant Features

The extraction of significant features performed by SURF based on sum of Haar wavelet responses in two directions (Brown, and Lowe, 2002). The Harris corner detection is the most widely used detector up to day due to its excellent results (Lindeberg, 2004). Fast-Hessian Detector is based on integral image and approximation. Integral image represents the sum of all pixels in the input image within a rectangular region formed by origin. Approximated Hessian detector uses box filter. While, scale variations are detected by different sizes of box filter. The next stage is to make descriptor of local gray level geometry feature. The local feature representing vector is made by combination of Haar wavelet response. The values of dominant directions are defined in relation to the selected region orientation.

The final stage of features extraction based on Canny edge detector (Canny, 1986), which is popular edge operator that widely used in digital image processing including remote sensing, and lines are extracted using Hough Transform (Duda, and Hart, 1975). Since SURF image of magnitude and direction is the base layer for feature detection, we propose to adjust several stages of Canny operator. In our work the four stages of Canny operator modified into three stages. Firstly, the image is smoothed by Gaussian convolution. We could skip the first derivative operator as it provides in the SURF image. Secondly, the process of non-maximal suppression (NMS) is imposed on the smoothed SURF image. Finally, the edge tracking process exhibits hysteresis controlled by two predefined thresholds. Traditional Canny operator carries on the edge tracking controlled by two thresholds, namely a high threshold and a low threshold. The tracking of one edge begin at a pixel whose gradient is larger than the high threshold, and tracking continues in both directions out from that pixel until no more pixel whose gradient is larger than the low threshold. The process is called hysteresis. It is usually difficult to set the two thresholds properly, especially for remote sensing image. The illumination and contrast of different portions of remote sensing image are often non-uniform.

The suggested process extracts long edges related to roads features with Hough Transform prior Canny operator. Thus roof detection could be implemented without predefined thresholds. As now the long edges related to roofs features and the edge tracking is carried out by inside edges. AS, it is difficult to detect continuous and stable edges solely from the images the morphological closing operation is employed. It's produced by the combination of dilation and erosion operations. During the process, the edges detected areas are integrated into the individual roof features. Finally, all the extracted features (roads and roofs) were converted from raster to vector format and saved as GIS project. While roofs converted to polygons, roads have been converted to polylines that cross-along the central line of detected (long edged) features.

2.2 Topological Method

Topological matching is usually used to reduce the search range or check the results of geometric matching, since it is seldom used alone. Topological methods can spread the matching into the whole network, but this requires high topological similarity of two data sets. Topological transfer method (Tomaselli, 1994) is representative of this type. If the polygons are matched, then according to the relationship of polygons and polylines, polylines to polylines matching can be deduced.

Data preprocessing stage standardizes the input data sets, ensures the conflation data sets have a same data format, the same north direction, and have overlapped spatial coverage. It also ensures the data sets have maximum similarity which is the basis of common objects matching.

A Reeb graph is a topological and skeletal structure for an object of arbitrary dimensions (Berg and Kreveld, 1997). In Topology Matching, the Reeb graph is used as a search key that represents shapes of the features. A node of the Reeb graph represents a connected component in a particular region, and adjacent nodes are linked by an edge if the corresponding connected components of the object contact each other. The Reeb graph is constructed by re-partitioning each region. The Multiresolutional Reeb Graph (MRG) begins with the construction of a Reeb graph having the finest resolution desired. Second, position of an inserted vertex is calculated by interpolating the positions of the relevant two vertices in the same proportion. Thirdly, the T-sets (connected components of triangles) are calculated. Fourthly, if two T-sets between adjacent ranges are connected, corresponding R-nodes are connected by an R-edge. The complete notification as follows: 1. R-node: A node in an MRG, 2. R-edge: An edge connecting R-nodes in an MRG, 3. T-set: A connected component in a region, 4. μn-range: A range of the function μn concerning an R-node or a T-set.

2.3 Weight-based Topological Map-matching

This subsection gives an overview of how similarity is calculated using MRGs. A weighting approach in selecting the correct feature from the candidates improves the accuracy of correct pair identification (Greenfeld, 2002). The suggested algorithm assigns weights for all candidates using similarity in linear network and transfer matching and selects the pair with highest weight score as the potentially corrected CPs. The mathematic representation of Root Mean Square (RMS) error value of map-matching process estimates accuracy of algorithm by predefined threshold. If the algorithm fails to identify the correct CPs pair among the candidate pairs and RMS error oversize threshold then the algorithm regenerates another pair with lower weight by an optional loop stage.

2.4 Test Point Error (TPE)

The cubic B-Spline convolution supports image transformation and resampling, as it is computed raw-by-raw and column-by-column (Unser et al., 1993). The results of proposed convolution tested with Test Point Error (TPE). The test points are CPs that were deliberately excluded from the calculation of the mapping parameters. The concept of this method can be extended such that the distance between corresponding 'test' lines or surfaces is measured (Nelson et al., 1997). TPE cannot be set to zero by overfitting. This method can be used only if a sufficient number of the CP's is available. Otherwise, the exclusion of several CP's may result in inaccurate estimation of mapping parameters. In our algorithm 10% of all CPs are excluded for TPE evaluation. Once again, if the algorithm fails to transform and resample sensed image and TPE error oversize threshold then the algorithm regenerates another pair with lower weight in stage 2 (Weight-based Topological Map-matching) by an optional loop stage.

3. RESULTS

The following section presents both simulated and real-world results. First, we evaluate the effect of multi-temporal

In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents   Author Index   Keyword Index

parameters settings and show the overall performance of the suggested AIRTop algorithm based on a standard evaluation set. Then, we evaluate the effect of multi-temporal and multi-sensor parameters. AIRTop has already been tested in a few real-world applications. Taking this application a bit further, we focus in this article on the more difficult problem of cameras calibration and temporal changes. AIRTop manages to calibrate the cameras even in challenging cases reliably and accurately.
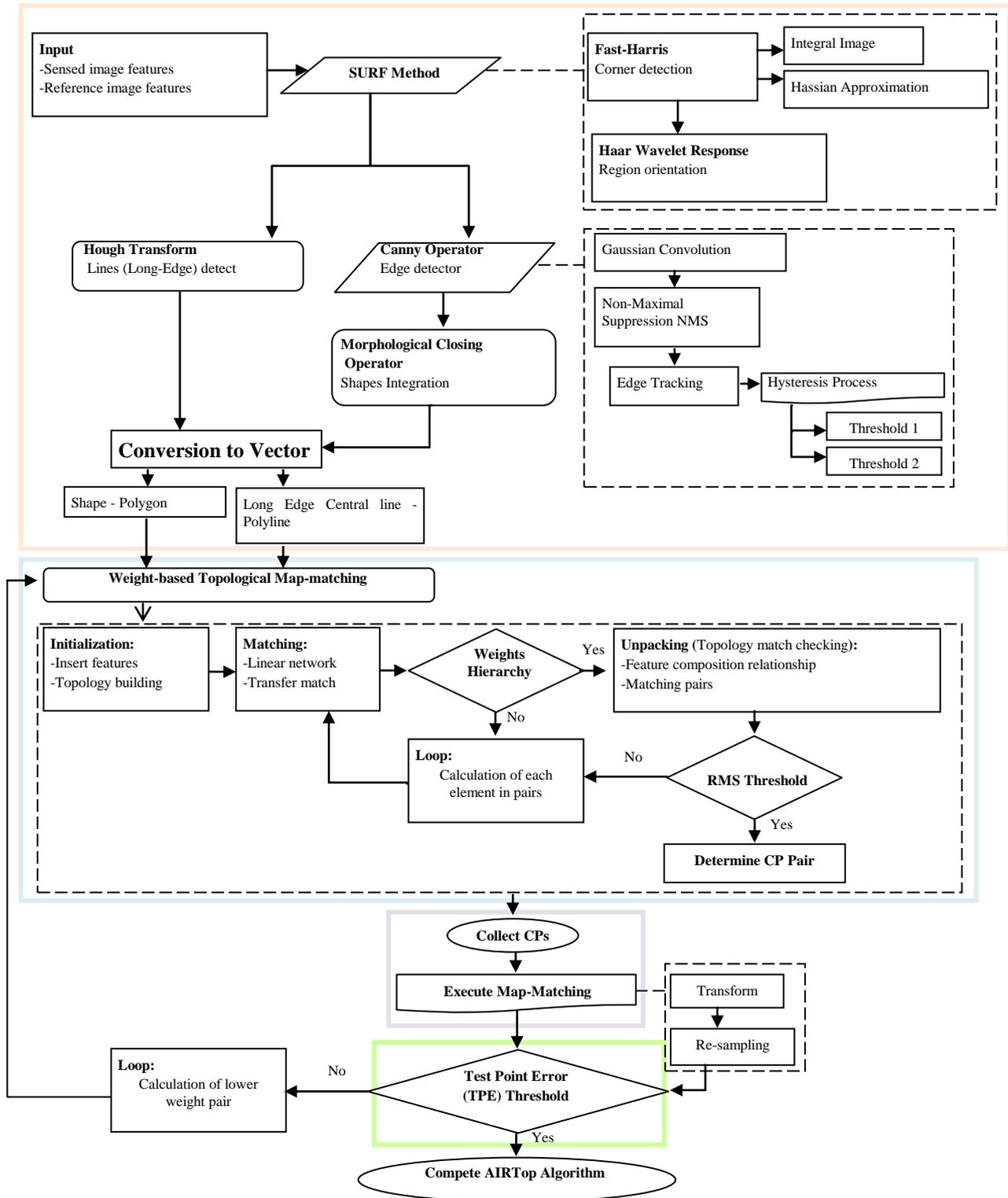
Figure 1. A flow-chart representing the AIRTop Algorithm, orange region is stage 1 (feature extraction), blue region is stage 2 (topology map-matching), purple region is stage 3 (matching process), green region is stage 4 (validation and accuracy)

In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents   Author Index   Keyword Index

3.1 Experimental evaluation

We tested our algorithm using the simulated images emphasizing the following: 1.Temporal changes simulated by adding and removing structures and lines, 2. Multi- sensor data simulated by different spatial resolution (rotation and scaling). The evaluation criterion is the repeatability score. Thus, the test sequences comprise images of real textured and structured scenes. Figure 2 shows that TPE with reasonable accuracy rate of >0.9 maintained for temporal change rate of < 40% of 26 simulated scenario of spatial variances including feature erasure and displacement. For cardinal changes (> 40%) the RMS threshold in stage 2 (topological map-matching) fails to identify the correct CPs pair.
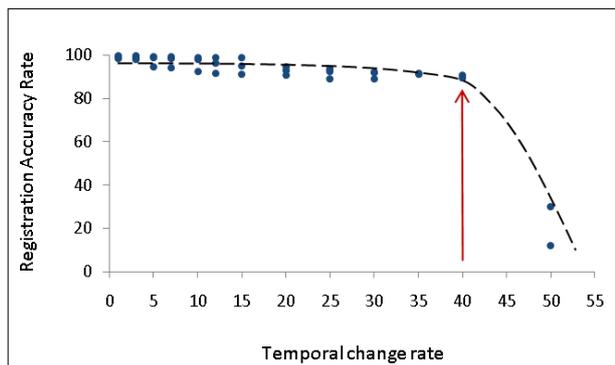
Figure 2. Temporal change versus registration accuracy, blue points are different simulation of temporal changes, black hatched line is trend line, and red cursor is RMS threshold of topological map-matching stage

An artificial scaling and rotation of simulated image evaluates matching accuracy for multi-sensor dataset. Table 1 summarizes the error in displacement, where TPE error represents Test Point error for 10% of all CPs pairs. The "Original" corresponds to original spatial resolution (0.1m) and orientation (0˚) of simulated image, "Sim1" corresponds to rotation of 100˚, "Sim1_1" corresponds to rotation of 100˚ and scaling of X2, "Sim2" corresponds to rotation of 290˚, "Sim2_2" corresponds to rotation of 290˚ and scaling of X2.5.

Simulated dataset	Original	Sim1	Sim1_1	Sim2	Sim2_2
TPE	0.00001	0.00032	0.0056	0.00038	0.0063

Table 1. Error (in m) for simulated multi-sensor dataset when original image resolution is 0.1 m and orientation is 0˚

3.2 Case Study

In this study we operated three sensors emphasizing multi-sensor registration in two selected time domains where multi-temporal changes were occurred. The selected sensors documented in table 2. Images of three sensors (table 2) was an area of 1.5X1.1 km in mid (33˚30' / 34˚42') Israel.

Sensor	Type	Detector	Spatial Resolution	Radiometric resolution	Date
Ikonos	Spaceborne	Pushbroom	1 m	11 bit	06.2008
Panchromatic scanner 1	Airborne	Pushbroom	0.25 m	12 bit	02.2009
Panchromatic scanner 2	Airborne	Whiskbroom	0.12m	8 bit	06.2009
Panchromatic scanner 2	Airborne	Whiskbroom	0.12m	8 bit	07.2009

Table 2. Selected sensors for case study

Table 3 summarizes the error in displacement of three images (Panchromatic scanner 1, and two Panchromatic scanner 2 images) to Ikonos image from 2008 where TPE error represents Test Point error for 10% of all CPs pairs.

Simulated dataset	TPE
Panchromatic scanner 1	0.001
Panchromatic scanner 2	0.0029
Panchromatic scanner 2	0.0035

Table 3. Error (in m) for simulated multi-sensor dataset when original images resolution is 1, 0.25, 0.12 m

4. CONCLUSION

We propose an AIRTop algorithm as method for the solution of the core problem of multi-sensor and multi-temporal images registration, based on combination between SURF (Speeded Up Robust Features) method and weight-based topological map-matching algorithm (tMM). The main focus of our algorithm is on scale and image rotation invariant the quality of the scanning system. Both simulated experimental and real-world case study results shows high accuracy of registration process.

5. REFERENCES

1.Berg, M., Kreveld, M., 1997. Trekking in the Alps without Freezing or Getting Tired. *Algorithmica*, 18, 306-323.

2.Brown, L. G., 1992. A survey of image registration techniques, ACM Computing Surveys. 24(4), 325-376.

3.Brown, H., Lowe, D., Invariant features from interest point groups, in BMVC, 2002.

4.Canny, J., 1986. A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8(6), 679-698.

5.Duda, R.O., Hart, P.E., 1975. Use of the Hough transform to detect lines and curves in pictures, *Association for Computing Machinery,* 15, 11-15.

6.Greenfeld, J.S., 2002. Matching GPS observation to location on a digital map. In: Preceedings of 81st Annual Meeting of the Transportation Research Board, Washington, DC.

7.Jensen, J. R., 2004. *Introductory digital image processing*, 3rd Ed., Upper Saddle River, NJ: Prentice Hall.

8.Lindeberg, T. 2004. Feature detection with automatic scale selection. "International Journal of Computer Vision", 30(2), 79-116.

9.Moigne, J. L., W. J. Campbell, and R. F. Cromp, 2002. "An automated parallel image registration technique based on the correlation of wavelet features". *IEEE Transaction on Geoscience and Remote Sensing,* 40(8), 1849-1864.

10.Nelson, S.J., Day, M.R., Buffone, P., Wald, L.L., Budinger, T.F., Hawkins, R., Dillon, W., Huhn, S., Prados, M., Chang, S., Vigneron, D.B., 1997. Alignment of volume mri and high resolution f-18 flurodeoxyglu-cose pet images for evaluation of

In: Wagner W., Székely, B. (eds.): ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7B

Contents   Author Index   Keyword Index

patients with brain tumors. *Journal of Computed Assisted Tomograph*y, 21, 183–191.

11.Tomaselli, L., 1994. Topological transfer: evolving linear GIS accuracy. URISA 1994 conference proceeding, 245-259.
12.Unser, M., Aldroubi, A., Eden, M., 1993. B-Spline Signal Processing: Part I Theory. *IEEE Transactions on Signal Processing*, 41, 821–832

13.Zitova, B. and J. Flusser, 2003, Image registration methods: a survey, *Image and Vision Computing*, 21(11), 977-1000.