IMPROVING HYSPEX SENSOR CO-REGISTRATION ACCURACY USING BRISK AND SENSOR-MODEL BASED RANSAC

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ABSTRACT:

To prepare for the hyperspectral satellite mission EnMAP (Environmental Mapping and Analysis Program)(Storch et al., 2010), the German Aerospace Center (DLR) acquired a HySpex camera from Norwegian company NEO in 2011(Baumgartner et al., 2012). For now this camera is mainly used to develop new and optimize existing processing methods for hyperspectral data, but in the future it will also serve to validate data produced by EnMAP. Similar to EnMAP, HySpex uses two separate sensors to acquire images in the SWIR and VNIR range of the electromagnetic spectrum. Both HySpex sensors use a FOV expander, resulting in an across track FOV of 27° and 34° for SWIR and VNIR respectively. The HySpex SWIR sensor has a pixel FOV of 0.75 mrad both in across and along track direction, while the HySpex VNIR sensor has a pixel FOV of 0.18 mrad in across track and 0.36 mrad in along track direction. The two sensors have slightly differing view angles, meaning they don't acquire the same area on the ground at exactly the same time. As the camera is mounted onto an airborne platform, the attitude during this fraction of time can deviate significantly (see Figure 1). In combination with the view angle difference, this mismatch leads to geometric co-registration inaccuracies between the SWIR and VNIR imagery. To correct this inaccuracy, the boresight angles between the two sensors have to be estimated precisely and the two scenes need to be orthorectified with the boresight angles taken into account. To estimate the boresight angles, first of all the two scenes need to be matched using a feature-detector. As the two sensor have spectrally overlapping channels, depending on the scene content, this step should usually result in a considerable amount of matches. After removing matching outliers and by applying the known sensor model, the boresight angles between the sensors can be estimated and the scenes can finally be orthorectified (Müller et al., 2005).

Figure 1: Orthorectified SWIR channel

There are several well-known matching algorithms which could possibly be used for the extraction of feature matches between the two scenes, e.g. Förstner(Förstner and Gülch, 1987), SIFT(Lowe, 2004), SURF(Bay et al., 2006). For this application however, we decided to test a relatively new method called BRISK (Binary Robust Invariant Scalable Keypoints)(Leutenegger et al., 2011). While the detection stage of BRISK is essentially a FAST(Rosten and Drummond, 2006) detector applied to a scale-space, the novelty of BRISK lies mostly in its binary descriptor which is based on gradients computed within a fixed sampling pattern. As the BRISK algorithm was designed with a focus on limited complexity, its developers promise similar or better matching performance than state-of-the-art algorithms such as SIFT or SURF at a significantly reduced runtime. One of the goals of this work was to investigate if these expectations can be met when applying the algorithm to HySpex data.

Due to the similarity between spectrally overlapping channels, it is often possible to find thousands of matches for one HySpex scene. In previous comparable processing chains, we removed outliers within these matches iteratively. In each iteration, the boresight angles were estimated by fitting the known sensor model to the matches and the match with the maximum deviation from this fit was removed. This process was repeated until the deviation of the worst match remained below a given threshold. While this method works very reliably if the number of outliers is not too big, due to the iterative approach, the runtime for thousands of matches can be very long. To reduce the runtime of the entire processing chain, this step was replaced by a RANSAC (Random sample consensus) (Fischler and Bolles, 1981) based approach. Instead of fitting the sensor model to all matches, it is fitted to a randomly selected subset and the resulting boresight angles are then tested against all matches. After a limited number of iterations, the estimated boresight angles which can be applied to most matches are accepted as the correct parameters. The two main advantages of this approach compared to the

previously used method are a reduction in runtime and a higher robustness against outliers in the match set.

Once the boresight angles have been estimated, the images of both sensors can be orthorectified independently and, assuming the matching worked, should be well registered to each other. To evaluate if this is the case, the entire processing chain was tested rigorously. According to our evaluation results the proposed use of BRISK for feature detection followed by sensor-model based RANSAC for outlier removal significantly improves the co-registration accuracy of the imagery produced by the two HySpex sensors.

REFERENCES

Baumgartner, A., Gege, P., Köhler, C., Lenhard, K. and Schwarzmaier, T., 2012. Characterisation methods for the hyperspectral sensor HySpex at DLR's calibration home base. In: SPIE Remote Sensing 2012, pp. 1–8.

Bay, H., Tuytelaars, T. and Van Gool, L., 2006. SURF: Speeded Up Robust Features. In: Computer Vision–ECCV 2006, Springer, pp. 404–417.

Fischler, M. A. and Bolles, R. C., 1981. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM 24(6), pp. 381–395.

Förstner, W. and Gülch, E., 1987. A fast operator for detection and precise location of distinct points, corners and centres of circular features. In: Proc. ISPRS intercommission conference on fast processing of photogrammetric data, pp. 281–305.

Leutenegger, S., Chli, M. and Siegwart, R. Y., 2011. BRISK: Binary robust invariant scalable keypoints. In: Computer Vision (ICCV), 2011 IEEE International Conference on, IEEE, pp. 2548–2555.

Lowe, D. G., 2004. Distinctive image features from scale-invariant keypoints. International journal of computer vision 60(2), pp. 91–110.

Müller, R., Lehner, M., Reinartz, P. and Schroeder, M., 2005. Evaluation of spaceborne and airborne line scanner images using a generic ortho image processor. In: Proc. of High Resolution Earth Imaging for Geospatial Information, ISPRS Hannover Workshop, Commision I WG, Vol. 5, p. 2005.

Rosten, E. and Drummond, T., 2006. Machine learning for high-speed corner detection. In: Computer Vision–ECCV 2006, Springer, pp. 430–443.

Storch, T., Eberle, S., Makasy, C., Maslin, S., de, A. M., Mißling, K.-D., Mühle, H., Müller, R., Engelbrecht, S., Gredel, J. and Müller, A., 2010. On the design of the ground segment for the future hyperspectral satellite mission EnMAP. In: IEEE Aerospace Conference Proceedings, Big Sky, MT, USA, 6-13 March, pp. 1 –11.

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