

# ROBUST FEATURE MATCHING AND SELECTION METHODS FOR MULTISENSOR IMAGE REGISTRATION

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## 1. INTRODUCTION

Multisensor image registration is necessary in many applications of remote sensing imagery, whose crucial problem is how to establish the correspondence between the features extracted from the reference and input images. Most existing methods only consider how to extract features, however, the quality of the features are ignored. In this paper, we combine scale invariant feature transform (SIFT) and maximally stable extremal region (MSER) to initialize a coarse-to-fine matching to extract plenty of control points(CPs) pairs. A concept of distribution quality (DQ) is introduced to measure the distribution of CPs pairs, and experimental analysis is conducted to analyze the effects of CPs pairs number and DQ on the registration root mean square error(RMSE). An automatic feature matching and selection algorithm is then introduced, extensive experiments demonstrate the effectiveness of the proposed algorithm by aligning real multisensor images.

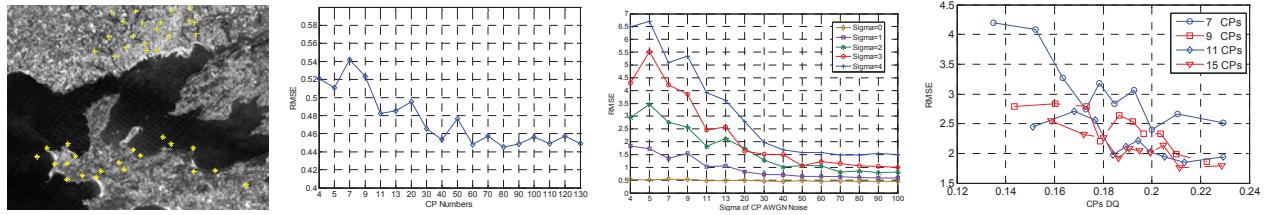
## 2. CONTROL PONTS QUALITY

The registration error is determined by two factors: the number and the distribution of the CPs. When CPs number is fixed, the distribution of CPs plays key role in registration. Zhu<sup>[1]</sup> indicated the strong relations lies between the probability of correct matching and information entropy(IE). Here, we introduce the concept DQ by means of the IE of CPs. For quantitative analysis, we compute the spatial distribution quality center of the CPs and DQ is calculated as (1).

$$(\bar{x}, \bar{y}) = \left( \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}, \frac{\sum_{i=1}^n w_i y_i}{\sum_{i=1}^n w_i} \right) \quad DQ = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2 + \sum_{i=1}^n (y_i - \bar{y})^2}{n}} / (M + N) \quad (1)$$

where  $w_i$  is the weight of CP  $i$ , IE of the CP is taken as the weight,  $M, N$  are the row and column numbers of the image. The bigger the DQ, the more spread out of the CPs; the smaller the DQ, the more concentrated of the CPs. As two groups of CPs with different distributions shown in Fig. 1(a), the DQ of the 20 CPs marked with “+” is 0.0712, while the DQ of the other 20 CPs is 0.1298.

In our experiment, we aim to analyze the effect of CPs number and DQ on the registration. To avoid the unknown transform model between unaligned image pair, we use one reference image and affine transform model to simulate the unaligned input image, and we select 200 CPs between the image pair(10 as test CPs). As non-manual CPs extraction methods may not achieve such accuracy as manual method, zero mean additive white Gaussian noise(AWGN) with different deviations are added into the CPs coordinates(no noise into test CPs). Fig 1 gives the results.



(a) Reference imag (b) CPs number effect without noise (c) CPs number effect with noise

(d) CPs DQ effect

Fig.1 CPs quality experiments

As shown in Fig. 1(b), RMSE decreases with the increasing of CPs number, but the curves aren't descending with increasing of CPs number all the time. When CPs number is bigger than 80, RMSE curves are almost flat. In Fig.1 (c), the RMSE of flat curves are in ascending order according to the sigma of AWGN due to the error of the CPs themselves. In Fig.1(d), the RMSE declines with the increasing of CPs DQ, but the curves are nearly flat when CPs DQ are bigger than 0.2. It means when CPs are more sparsely distributed, the registration RMSE is smaller , however, there is a threshold for the decreasing of the RMSE.

## 3. HIERARCHICAL FEATURE MATCHING AND SELCETION STRATEGY FOR REGISTRATION

Mikolajczyk<sup>[2][3]</sup> made a performance evaluation of popular local descriptors and region detectors, the results shown that

SIFT outperformed other descriptors and MSER obtained the highest score in many cases among popular detectors. Here, we combine SIFT and MSER to construct a robust coarse-to-fine matching for multisensor image registration, Fig. 2 give the framework of our method.



Fig. 2 Coarse-to-fine framework for registration

### 3.1. Coarse Matching Using SIFT and MSER

Lowe<sup>[4]</sup> established an Euclidean distance upper bound threshold 0.6 and only considered the matches below this threshold. Indeed, we sort the matches by the distance ,select the top 10 in order. We also use Matas's MSER to detect regions. To describe the corresponding MSER regions with nonlinear intensity changes from multisensor images(eg. EO/SAR), distribution-based descriptors (eg. SIFT descriptor) are not suitable for their strongly dependence on the image intensities, so Hu's 7 invariant moments are used. We use the bidirectional matching to find the matched MSER regions, and the Euclidean distance threshold for 7 invariant moments is set to 1.2 experimentally. After coarse matching, the input image is coarsely aligned with affine model.

### 3.2 Fine Matching Based on Coarse Matching

For multisensor images, coarse matching may only find handful CPs pairs, which are insufficient for accurate registration. Since the pixel intensities of multisensor images may vary dramatically and resolutions are different, we use several scale spaces and harris-like detector to detect all the possible corners in the coarse aligned images, then the CPs are matched with mutual information.

### 3.3 Hierarchical Selection Strategy Based on CPs Distribution Quality

As our fine matching algorithm finds plenty of CPs , and the registration RMSE depends on the CPs number and DQ, a hierarchical CPs selection strategy based on DQ is introduced. We divide the image into subgrids, set the maximum CPs number for every subgrid, delete the CPs with small IE in every grid according to the DQ. The selected CPs are used for the fine registration.

## 4. EXPERIMENTAL RESULTS

We have applied this algorithm to align EO/EO image pair (<http://vision.ece.ucsb.edu/registration/satellite>) and EO/SAR images and we also compare our results with Li<sup>[5]</sup>. For accuracy evaluation of our algorithm, we randomly select a set of 10 CPs as independent checking points in reference and input images. We calculate the error in X , Y coordinates and RMSE of Li's and ours. Our maximum error is 1.364 pixels among all the checking points, and the RMSE is 0.620, while Li's results are twice of ours. The RMSE with our unselected CPs is 0.718, which show the effectiveness of the selection. We do the experiments with the other 9 image pairs from UCSB website, the RMSE results of our algorithm are around 0.5, but the RMSE of Li's algorithm is more than 1 pixel. We also use our algorithm to align EO/SAR images of the Forbidden City of Beijing, the RMSE achieves 1.582, which is acceptable in most of the applications.

## 5. CONCLUSION

In this paper, we presented a robust approach for multisensor image registration. The core of the approach is the coarse-to-fine strategy which combined SIFT and MSER in coarse matching and CPs DQ based selection after fine matching. The performance of the proposed algorithm has been demonstrated by aligning various images, including EO/EO and EO/SAR images. The proposed algorithm outperforms a lot than classic contour-based algorithm, and the registration error is acceptable for most application.

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## 11. REFERENCES

- [1] Q. Zhu, B. Wu, N. Wan, Z. X. Xu, "An interest point detect method to stereo images with good repeatability and information content," *Acta Electronica Sinica.*, vol. 34, no.2, pp. 205-209,2006
- [2] K. Mikolajczyk, C. Schmid, "A performance evalution of local descriptors," *IEEE Tranaction on Pattenn Analysis and Machine Intelligence*, vo27,no.10,pp.1615-1630, May. 2005
- [3] K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir, L. Vangool, "A comparison of affine region detectors," *Internation Journal of Computer Vision*, vo65, no.1-2,pp.43-72, Nov. 2005
- [4] D. Lowe, "Distinctive image features from scale-invariant keypoints," *International Journal of Computer Vision*, 60, 2 pp. 91-110, 2004.
- [5] H. Li, B. S. Manjunath, S. K. Mitra, "A contour based approach to multisensor image registration," *IEEE Transactions on Image Processing*, vo4,no.3,pp.320-334, Mar. 1995