

A NOVEL HOG-BASED TEMPLATE MATCHING METHOD FOR SAR AND OPTICAL IMAGE

Deyu Song^{1,2}, Lan liu^{1,2}, Xiangyin Zhang^{1,2}, Kaiyu Qin^{1,2}, Libo Wang^{1,2}

¹School of Aeronautics and Astronautics, University of Electric Science and Technology of China, Chengdu 611731, China

²Aircraft Swarm Intelligent Sensing and Cooperative Control Key Laboratory of Sichuan Province, Chengdu 611731, China

ABSTRACT

Due to multiplicative speckle noise in Synthetic Aperture Radar(SAR) image and significant intensity difference between different data, it is difficult to match SAR and optical image accurately. In this paper, we propose a novel template matching method for SAR and optical image named multi-Dimensional Matching Histogram of Oriented Gradient (mDM-HOG). Firstly, in order to reduce the negative effect of speckle noise on gradient calculation, the ratio of exponentially weighted averages(ROEWA) operator is introduced to calculate the gradient magnitude and orientation in SAR image. Then, using the obtained gradient information, we extract the 3-D pixelwise HOG feature for both images. Finally, we separate the 3-D feature map to nine sub-maps and measure the similarity of the sub-maps to obtain the template matching result. The experimental result shows that in comparison with the existing methods, the proposed template matching method has higher accuracy when locating the position of SAR image in optical image.

Index Terms— template matching, SAR and optical image, HOG, similarity measure

1. INTRODUCTION

With rapid development of remote sensing imaging technique, diverse modalities of image data[e.g., optical, infrared, the synthetic aperture radar(SAR)] can be acquired. But practically, it is difficult to obtain multi-modal images from the same region at the same time due to the constraint of imaging technique[1]. Hence, the matching of heterologous images plays a key role in integrating information obtained from different imaging sensors. Due to the vast difference of imaging principle, there is significant intensity difference between SAR and optical images, as shown in Fig.1, which results low accuracy in SAR and optical image matching tasks.

Generally, image matching methods can be classified into two categories: feature-based method and template-based method. The feature-based image matching methods are usually based on extracting reliable feature and establishing

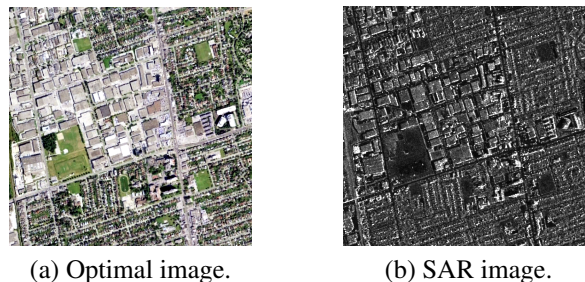


Fig. 1. The structre features between SAR and optical image are similar under signifciant intensity difference.

matches between feature pairs. In spite of the enormous advantage on operational speed, the feature-based matching methods are extremely dependent on the validity(including stability, distinctness and repeatability) of extracted feature between SAR and optical images and not robust to noise[2]. Different from feature-based methods, template-based methods involve defining a specific similarity measure process to identify the template image in a larger image by performing the matching operation. Classical template matching methods such as the sum of squared differences (SSD), the normalized cross correlation (NCC)[3] and the mutual information (MI)[4] show low robustness in multi-modal image matching because these methods use only intensity information for calculation, while there are significant intensity difference between different modal of images. Compared with intensity information, the structure features like Histogram of Oriented Gradient(HOG)[5] are far more resistant to intensity discrepancy. The HOG descriptor has been introduced in SAR and optical matching tasks[6] but the matching accrcy still requires improving.

In this paper, we propose a novel template matching method for SAR and optical image named mDM-HOG. To reduce the impact of noise in SAR image, the ratio of exponentially weighted averages(ROEWA)[7] operator is used for gradient computation, and a 3-D pixelwise HOG feature map is extracted using the obtained gradient information.

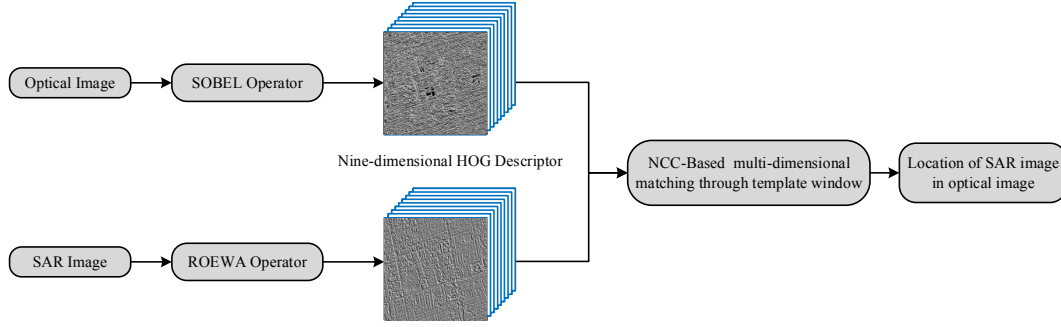


Fig. 2. The flowchart of proposed mDM-HOG.

Moreover, a novel multi-dimensional matching method is proposed to improve the matching accuracy. The extracted 3-D feature map is separated to nine sub-maps, by measuring the similarity in sub-maps, the position of SAR image in the optical image can thus be located.

2. METHODOLOGY

In this section, we will introduce the details of proposed template matching method mDM-HOG and the design of three procedures that compose the matching process. The flowchart of our method is as illustrated in Fig.2.

2.1. Gradient Computation

In many classical matching methods, the use of gradient by derivative is unstable due to multiplicative noise in SAR images. For SAR images, the ratio-based gradient operators such as the ratio of average (ROA) [8] have been proved more constant than derivative-based ones. Based on ROA, a method named ROEWA was designed for SAR image segmentation and shows more robustness to noise than the ROA does [7]. In the first stage, we introduce the ROEWA operator as the gradient computation for SAR image. Herein, the ratio and gradient on direction are defined as

$$R_{d,\sigma} = \log \left(\frac{\int_{x=R} \int_{y=R^+} I(i+x, j+y) \times e^{-\frac{|x|+|y|}{\sigma}}}{\int_{x=R} \int_{y=R^-} I(i+x, j+y) \times e^{-\frac{|x|+|y|}{\sigma}}} \right) \quad (1)$$

$$G_{d,\sigma} = \max \left(R_{d,\sigma}, \frac{1}{R_{d,\sigma}} \right) \quad (2)$$

where $G_{d,\sigma}$ is the gradient on horizontal or vertical, σ is the exponential weight parameter which can smooth the SAR image adaptively. Thus, the gradient information of SAR image can be obtained.

The comparison of gradient orientation in Fig.1(b) computed by ROEWA operator and classical derivative-based operator is as shown in Fig.3. It appears that the ROEWA oper-

ator performs far better at distinguishing gradient orientation than the derivative-based operator does.

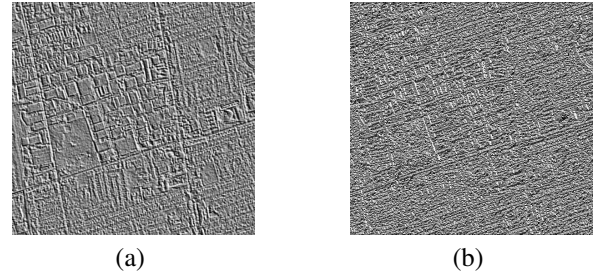


Fig. 3. The comparison of different gradient computations for SAR image in Fig.1(b). (a) Gradient orientation by ROEWA. (b) Gradient orientation by derivative.

For optical image, we use Sobel operator to extract gradients. Thus, the computed gradient information will now help us to construct robust feature representation for both SAR and optical images.

2.2. Construction of HOG Descriptor

In this stage, we aim at extracting robust structure feature from both SAR and optical images through HOG feature representation. First, we divide the image into several overlapping blocks, each block consists of 3×3 cells, which contains 8×8 pixels. In each cell, the gradient orientation is divided into nine bins. Then, weighted by trilinear interpolation method, the histogram bins of the block can be constructed from the weighted sum of gradient magnitudes of every single pixel in every single cell. Finally, according to nine orientation bins, the 3-D pixelwise HOG feature representation can be collected.

We would like to describe the extracted pixelwise HOG feature representation as a 3-D one, because the feature representation for a pixel (x, y) is a vector $\vec{z} = [h_1, h_2, \dots, h_9]^T$ contains histogram information from nine different orientations. According to the orientations, the 3-D pixelwise HOG feature representation will then be separated to nine 2-D fea-

ture sub-maps, each sub-map contains histogram information from just one orientation.

2.3. NCC-based matching method

In the last stage, we propose a novel multi-dimensional matching method for the 3-D pixelwise feature representation. Our method consists of three operations: sub-map construction, NCC similarity measure and mis-matching points exclusion. The flowchart of the proposed method is illustrated in Fig.4.

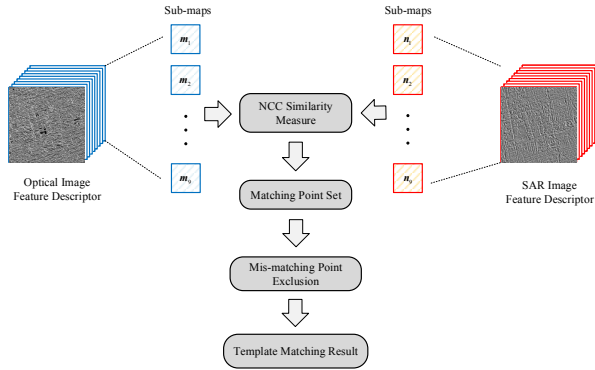


Fig. 4. An overview of proposed multi-dimensional matching method.

First, according to orientations, we separate the pixelwise HOG feature representation to nine 2-D feature sub-maps. Then, the NCC similarity is addressed in nine sub-map pairs. Since the histogram of different orientations remains high similarity, the similarity maps calculated in the sub-maps are similar as well. Through sliding template window, we select four max matching points in each similarity map, which is obtained by the sub-map pairs. Herein, we define the situation that the selected four points are each others neighbor a good matching result. Finally, by computing the Euclidean Distance between selected points, the mis-matching points are removed and the good matching points are reserved as part of the final matching point set. After obtaining the matching point set, the final template matching result is obtained by calculating means of two closest matching points in the point set.

3. EXPERIMENTAL RESULT

In this section, we evaluate the proposed template matching method mDM-HOG on 193 pairs of SAR and optical images. All test images are from the public Sentinel SAR-optical dataset named SEN1-2[9], which contains corresponding SAR-optical image patches in size of 256×256 pixels. The mDM-HOG is compared with the classical NCC, and the state-of-the-art CARMI[10], HIM-Net[11] methods. Using the same-size template images(150×150 pixels, all template

images are captured randomly from full SAR image), the Correct Matching Rate(CMR) and the average error of correct matches are chosen to measure the matching accuracy of these methods. The CMR value is calculated by dividing the number of correct matching image pairs by the total number of image pairs. The average error of correct matches is the mean value of the Euclidean Distance between correct matching result and corresponding ground truth. Some of the SAR and optical image template matching results are shown in Fig.5.

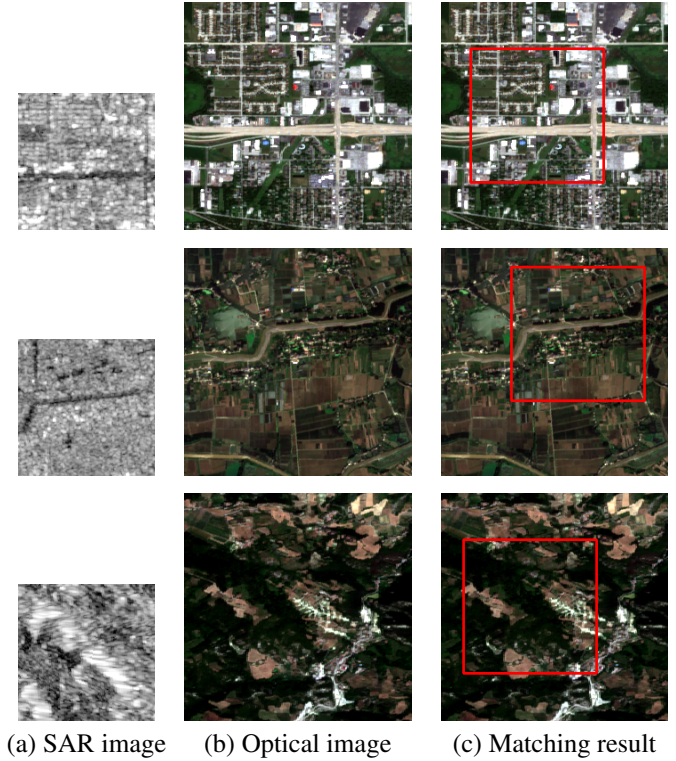


Fig. 5. The matching result of mDM-HOG on the SEN1-2 dataset.

Table 1 compares our method with three other methods by measuring the CMR value and the average error of correct matches. It can be observed that the proposed nDM-HOG performs the best, with lowest average error of correct matches at 1.16 pixels. While the CMR of HIM-Net is a little bit higher than our mDM-HOG, the average error of correct matches of our method performs 0.15 pixels lower. The error distribution of four methods is as shown in Fig.6. The proposed mDM-HOG has the most distribution below 1 pixel with the least distribution above 4 pixels. In our experiment, we noticed that most failed-matching images contain repetitive objects[e.g. roads, farms] and flat intensity variation regions. Some of these failed-matching situations can be solved through changing the cell size, for example, replace the 8×8 pixels cell by a 4×4 pixels one. But in most test image pairs, our method shows strong robustness to multiple speckle noise

in SAR images and performs better on accuracy than the other three methods.

Table 1. Comparison of Template Matching result

Method	CMR(%)	Average error of correct matches (pixels)
NCC	7.25(%)	9.44
CARMI	40.93(%)	3.24
HIM-Net	74.61(%)	1.31
mDM-HOG	73.59(%)	1.16

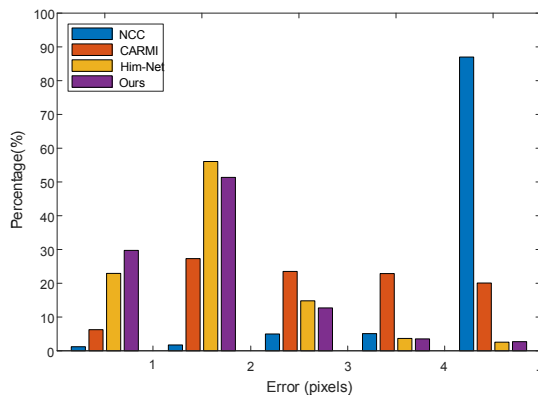


Fig. 6. Error distribution of four template matching methods.

4. CONCLUSION

In this paper, we have proposed a novel HOG-based template matching method for SAR and optical image named mDM-HOG. The massive amount of multiplicative speckle noise in SAR image has been effectively inhibited by introducing ROEWA operator to compute gradient magnitude and orientation, and the structure features for every pixels in image is extracted by a 3-D pixelwise HOG feature representation. Moreover, a novel multi-dimensional matching method has been proposed by separately computing similarity between feature sub-maps. The experimental result indicates that the proposed mDM-HOG can accurately locate the position of SAR image in corresponding optical image and outperforms the NCC, CARMI and HIM-Net methods. In future research, we will focus on the time-costing problem and try to improve robustness under specific situations.

5. REFERENCES

[1] Qingbo Ji, Lingjie Wang, Changbo Hou, Qiang Zhang, Qingquan Liu, and Yue Jiang, "Sar and optical im-

age matching eased on phase congruency and template matching," in *2021 8th International Conference on Dependable Systems and Their Applications (DSA)*, 2021, pp. 315–320.

- [2] M. Gesto-Diaz, F. Tombari, D. Gonzalez-Aguilera, L. Lopez-Fernandez, and P. Rodriguez-Gonzalvez, "Feature matching evaluation for multimodal correspondence," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 129, pp. 179–188, 2017.
- [3] J.N. Sarvaiya, Suprava Patnaik, and Salman Bombaywala, "Image registration by template matching using normalized cross-correlation," in *2009 International Conference on Advances in Computing, Control, and Telecommunication Technologies*, 2009, pp. 819–822.
- [4] S. Suri and P. Reinartz, "Mutual-information-based registration of terrasars-x and ikonos imagery in urban areas," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 2, pp. 939–949, 2010.
- [5] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, 2005, vol. 1, pp. 886–893 vol. 1.
- [6] Qing Li, Guangzhou Qu, and Zengliang Li, "Matching between sar images and optical images based on hog descriptor," in *IET International Radar Conference 2013*, 2013, pp. 1–4.
- [7] R. Fjortoft, A. Lopes, P. Marthon, and E. Cubero-Castan, "An optimal multiedge detector for sar image segmentation," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 36, no. 3, pp. 793–802, 1998.
- [8] R. Touzi, A. Lopes, and P. Bousquet, "A statistical and geometrical edge detector for sar images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 26, no. 6, pp. 764–773, 1988.
- [9] M. Schmitt, L. H. Hughes, and X. X. Zhu, "The sen1-2 dataset for deep learning in sar-optical data fusion," 2018.
- [10] Sahil Suri and Peter Reinartz, "Mutual-information-based registration of terrasars-x and ikonos imagery in urban areas," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 2, pp. 939–949, 2010.
- [11] Haoran Xu, Mingyi He, Zhibo Rao, and Wenyao Li, "Him-net: A new neural network approach for sar and optical image template matching1," in *2021 IEEE International Conference on Image Processing (ICIP)*, 2021, pp. 3827–3831.