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Feature Extraction and Matching in Optical and SAR Image

L. Manisha Rani

UG Student, Sansakrithi school of engineering, India

Abstract

In general, the gradient descriptor is a widely used method for matching remote sensing images. However, in the case of optical-to-synthetic aperture radar (SAR) matching there exists the non-linear intensity differences where the gradient descriptor is not able to handle these differences. Moreover, optical-to-SAR matching methods based on structural information of image are also not effective for the images consisting of large geometric differences. So, to overcome these limitations, a new method based on the structural descriptor has been proposed. Since the existing structural descriptors are capable of handling small geometric differences with zero orientations, the proposed method has been used to handle the non-linear intensity differences and it can increase the number of matching points as compared to previous methods.

Keywords: Descriptor, image matching, non-linear intensity differences.

INTRODUCTION

Image matching is the method involved in analyzing two images mathematically such that matching of pixels in the two image matches to a similar actual district of the area being imaged [1,2]. Coordinating calculations assumes a vital part in choosing correspondences between two image scenes. The matching calculations are of two sorts of area based algorithm and feature based algorithm. In the remote sensing areas automatic image matching between multimodal images has become a toughest task because of its non linear radiometric differences between them [1]. A local Self Similarity (LSS) [3] based nearby descriptor called Distinctive Order based Self-Similarity Descriptor (DOBSS) has been introduced for powerful multi-sensor remote detecting picture coordinating [4]. The proposed descriptor comprises of the accompanying advances: Uniform Robust Scale Invariant Feature Transform (UR-SIFT) highlight extraction, relationship surface calculation, direction task utilizing relationship surface histogram, nearby area distributing, last descriptor calculation in light of maximal and middle connection. The principle invariance property of the proposed descriptor is its heartiness against the light distinctions of the highlights in the multi modular remote detecting pictures. Test results on an assortment of multi-sensor satellite picture sets uncover that DOBSS shows better review, accuracy, and positional precision than different descriptors including SIFT, Partial Intensity Invariant Feature Descriptor (PIIFD), Gradient Location and Orientation Histogram (GLOH), Local Intensity Order Pattern (LIOP), and furthermore standard LSS [5-8]. Registering an Optical-to-synthetic aperture radar (SAR) image is a challenging task on the remote sensor as images have significant non-linear variations and magnitude geometric differences [1, 9]. In addition, the effect of specter noise on the SAR image continuously affects the registration result. Structural definitions are very effective in handling non-linear variability between optical images and SAR. Although there are many ways to register photos to SAR have been proposed over the past few years based on image layout details, but most of which do not apply to large images geometric differences. To address these issues, the image enrollment of the novel goes to SAR. The algorithm is proposed using a new structural adjective. Initially, the features in the corner are extracted from optical and SAR images [8]. The enlistment of SAR and optical pictures is a provoking undertaking because of the potential nonlinear power contrasts between the two pictures. In this paper, a clever picture enlistment strategy, which joins nonlinear dissemination and Phase Congruency Primary Descriptor (PCSD) [10], is proposed for the enrollment of SAR and optical pictures. In the first place, to lessen the impact of spot commotion on include extraction, a Uniform Nonlinear Dispersion based Harris (UND-Harris) highlight extraction technique is planned. The UND-Harris indicator is created in light of nonlinear dissemination, includes extent, and square technique, and investigates a lot more all around dispersed element focuses with capability of being accurately coordinated. Then, at that point, as per the property that primary elements are less delicate to methodology variety, a clever underlying descriptor, specifically, the PCSD, is developed to vigorously depict the characteristics of the separated places.

PROPOSED METHOD

Usually a similarity operator is used to find out the similarity between the two matrices. There are many parameters which are helpful to find out the similarity between two matrices, the following are the list of operators that are used to find the similarity between two matrices.

A. *Trace*

The trace is related to the derivative of the determinant A

$$\Delta A = \sum_{i,j=1}^{n} a_{ij} \tag{1}$$

,

where, a_{ij} denotes the entry on the ith row and jth column of A. Suppose A and B are two square matrices of size n, then A and B are similar if there exists a non singular matrix S of size n, such that $A = S^{-1}BS$.

B. *Rank*

A matrix is said to be of rank zero when all of its elements become zero. The position of the lattice is the component of the vector space got by its segments. The position of a framework can't surpass more than the quantity of its lines or segments. The position of the invalid network is zero. In the event that two grids are comparable, they have a similar position. The rank, of the null matrix is zero. If two matrices are similar, then they have the same rank. Let us consider three diagonal matrices A, X, and Bthen we have rank(XB)=rank(B) and rank(AX)=rank(A) and $X^{-1}AX = B$ which implies $AX = XB$. Therefore, rank(A)=rank(B).

C. *Eigen values and Eigen vectors:*

Geometrically, an eigenvector, corresponding to a real nonzero eigenvalue, points in a direction in which it is stretched by the transformation and the eigenvalue is the factor by which it is stretched. If two matrices are similar, they have the same eigenvalues and the same number of independent eigenvectors (but probably not the same eigenvectors).

D. *Determinant*

The determinant of a matrix is the signed factor by which areas are scaled by this matrix. If the sign is negative the matrix reverses orientation. All our examples were two-dimensional. Two square matrices are said to be similar if they represent the same linear operator under different bases. Two similar matrices have the same rank, trace, determinant and eigen values.

E. *Actual proposed method*

Above all the parameters mentioned, all of them are not useful to find the similarity between the matrices because we need an operator that shows the percentage of similarity between the two matrices. One of such operator is the Oriented Features from Accelerated Segment Test (FAST) [11] Rotated Binary Robust Independent Elementary Features (BRIEF) [12] called as ORB [13] and for matching we used the Brute-Force Matching [14] Algorithm.

F. *Feature extraction*

Usually feature extraction is a process which is used to locate the structural descriptors. In ORB algorithm which is having Harris operator which is used to locate key points in the input images. Sphere locator represents ORB, this is liberated from cost calculation, the advantage of this calculation is that it doesn't need Graphics Processing Unit (GPU), it can register on ordinary CPU. Sphere is fundamentally the mix of two calculations included FAST and BRIEF. Sphere locator first uses FAST calculation which observes the central issues then, at that point, applies Harris corner measure to observe top N quantities of central issues among them, this calculation rapidly chooses the central issues by looking at the unmistakable districts like the force varieties. Presently the job of BRIEF calculation comes, this calculation takes the central issues and transform into the parallel descriptor/paired element vector that contains the blend of 0s and1s as it were. The central issues established by FAST calculation and descriptors made by BRIEF calculation both together address the item. BRIEF is the quicker technique for highlight descriptor computation and it additionally gives a high acknowledgment rate until and except if there is enormous in-plane revolution

G. *Feature matching*

Feature matching is the method involved with adjusting various arrangements of pictures procured from various view points, at various times or from various sensors. It has an assortment of uses like picture combination and change discovery. A precise arrangement of optical and SAR pictures is as yet a complicated assignment because of the presence of enormous force varieties and mathematical contrasts between the pictures. Another significant component is that the SAR pictures normally tainted by the multiplicative spot commotion and a s result, it the extremely challenging to track down adequate matching sets. The strategies for optical-to-SAR picture enlistment can be isolated into gatherings: power based techniques and element based strategies. Force based strategies utilize the pixel power of the information pictures, to enroll the optical and SAR pictures. Be that as it may, these are extremely tedious techniques. The component based strategies recognize the invariant highlights like corners, lines, and bends. Harris corners are the notable component extraction administrator in picture enlistment techniques. In any case, it has no descriptor to match the elements. Brute-Force Matching is the well known methodology for remote detecting picture enlistment. Yet, the standard Brute-Force Matching highlights are not consistently appropriated over the pictures and the presentation of the Brute-Force Matching descriptor corrupts in optical-to-SAR picture enlistment. In another adaptation of the Brute-Force Matching descriptor calculation can be observed which is utilized for the homogeneous conveyance of the Brute-Force Matching highlights

SYSTEM MODEL

The flowchart of the algorithm involved during the feature extraction and feature matching process is shown in Fig. 1

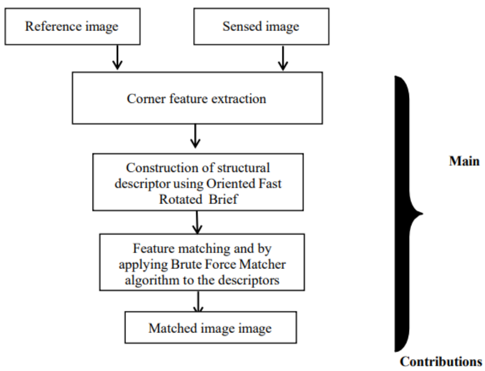
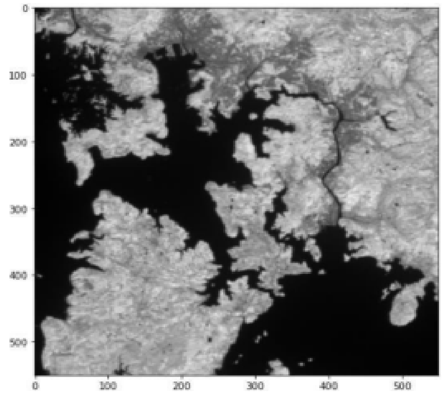


Fig. 1: Flowchart of proposed method .

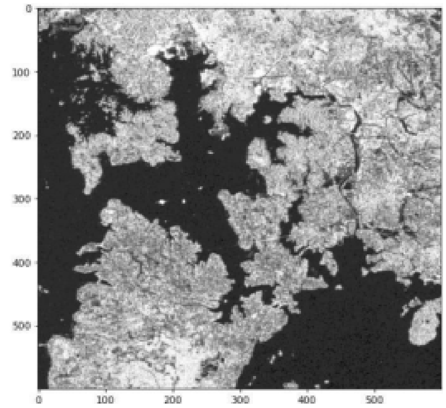
At first we take two input images named optical and SAR as reference and sensed .Then we extract corner features named as key points for the input multimodal images. Then we construct structural descriptors for the each of the corner feature or the key point. In the next step, we apply oriented fast rotated brief for the extracted corners of the input images. Then Brute-Force Matching algorithm is used to match the input corners that have more similarity or any kind of orientations between them. At the end, we get the matching percentage between the images

H. Simulation Results

The simulation has been performed using OpenCV in python. Fig. 2 shows the pictures, we will use to create the Brute-Force Matching highlights. To start with, we need to develop a Brute-Force Matching article and afterward utilize the capacity to distinguish and compute in order to get the keypoints. It will return two qualities - the keypoints and the descriptors. Then, we should attempt to coordinate the elements from image 1 [Fig. 2(a)] with highlights from image 2 [Fig. 2(b)]. We will be utilizing the capacity match() from the Brute-Force Matcher module. Additionally, we will define boundaries between the highlights that match in both the pictures. Next, we will try to match the features from image 1 with features from image 2. We will be using the function match() from the Brute-Force Matcher module and also, we will draw lines between the features that match in both the images. This can be done using the drawmatches() function in OpenCV. Bruce-Force Matcher is utilized for coordinating the elements of the principal picture with another picture. It takes one descriptor of first picture and matches to every one of the descriptors of the subsequent picture and afterward it goes to the second descriptor of first picture and matches to all the descriptor of the subsequent picture, etc. Fig. 3 shows the matching points between the two images shown in Fig. 2. Fig. 4 shows the matching results obtained from previous methods namely Single-Surface Phase Congruency based Self Similarity (SS-PCSS) [9], Filtered SS-PCSS [9], Filtered Multi-Surface (MS)-PCSS and the proposed method considering a dataset 1. Fig. 5 shows the total number of matching pairs available after performing the feature matching operation in this presented work.



(a)



(b)

Fig. 2. (a) SAR image which is a reference image, (b) Optical image which is a sensed image

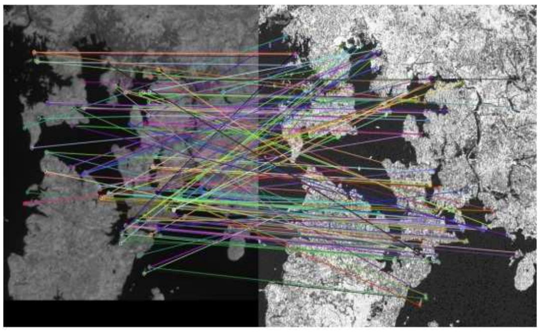


Fig.3. Feature matching of SAR and optical images.

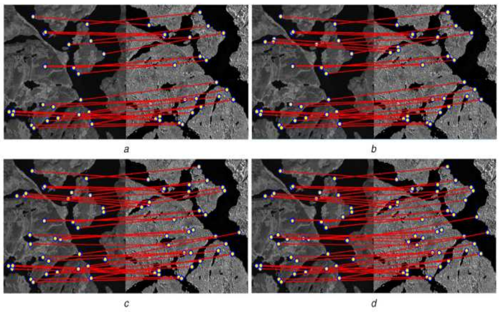


Fig. 4. Matching results of (a) SS-PCSS, (b) Filtered SS-PCSS, (c) Filtered MS-PCSS, (d) Proposed method for the data set 1.

```
Descriptors of Image 1 [[124  39  42 ... 123 254  66]
 [ 88 185  27 ...   0 167 122]
 [120  50  28 ...   0   2  35]
 ...
 [ 89  56 186 ... 128  67  83]
 [ 26 222 110 ... 245  53 251]
 [144  20  63 ...  64   5  83]]
Descriptors of Image 2 [[ 41 249  19 ...   2  67 184]
 [ 44 248 250 ...  90 207 243]
 [216 242 222 ... 128  15  11]
 ...
 [ 40 249  57 ...  24 198 162]
 [218 207  27 ... 147  45  59]
 [156 221  46 ...  31 188 242]]
------------------------------
Shape of descriptor of first image (500, 32)
Shape of descriptor of second image (500, 32)
```

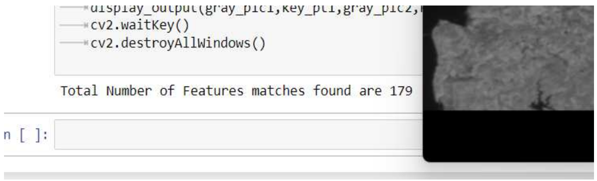


Fig. 5. Total number of matching pairs after performing the matching operation

CONCLUSION

An optical-to-SAR image registration/matching technique is proposed in this work for registering the optical and SAR pictures with large geometric differences. Earlier, the Harris function is used to retrieve the corner features from the input images. The retrieved features are initially uniformly distributed by the Brute-Force Matching algorithm. Then, using Adapted Anisotropic Gaussian (AAG) filters are employed upon input images which reduce the effect of speckle noise. Further, the estimation of dominant features are established and a structural descriptor is constructed for each of the extracted features. In this work, a novel approach is proposed that enhance the distinctiveness of the structural descriptor. This proposed method can enhance the matching point results. From the simulation results, it can be inferred that the proposed method provides better registration results than the other structural descriptors such as LSS and DOBSS. Here, an ORB algorithm and Brute-Force Matching algorithm is used which gives better matching rate as compared to previous methods by providing 178 matches in this proposed method.

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