Remote Sensing Image Registration Using Modified SIFT Algorithm And Efficient Outlier Detection Method

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Abstract—**Image Registration is a fundamental image processing technique for aligning two or more partially overlapping images of the same scene taken from different sensors, at different times, at different depths, or from different viewpoints so that it can be made to form one panoramic image comprising the whole scene. The registration geometrically aligns two images (the reference and sensed images). Image registration also called image alignment algorithm can be classified into area-based and feature based. Due to the large image size with local distortion satellite image registration uses feature based methods. Scale-invariant feature transforms (SIFT) have been widely applied to register satellite images, which provide robust features. But the registration accuracy is affected by the lack of features and low-distribution quality. This technique also suffers from a high-computational cost. A new feature based image registration technique is proposed in which the entire image X*Y be divided into smaller image blocks M*N to process it in order to improve the accuracy as well as to extract more distinctive features. This paper proposes an automatic registration technique based on modified Scale Invariant Feature Transform (SIFT) features, which can deal with the large variations of scale, rotation and illumination of the images. Moreover an efficient outlier removal method based on the consistency of dominant orientation of feature points is proposed in this paper which will increase the accuracy.**

Keywords— Image registration, SIFT, dominant orientation

I. Introduction

Image registration [1] is a challenging task, which has wide applications in survillence, motion estimation, and fusion systems. It is required in remote sensing applications for multispectral classification, change detection, image mosaicing, weather forecasting, creating super resolution images, multispectral classification .It is the process of aligning two or more partially overlapping images of the same scene taken from different sensors, at different times, at different depths, or from different viewpoints so that it can be made to form one panoramic image comprising the whole scene. This process designates one image as the reference or the fixed image, and the other image as the input image or the unregistered image. The reference image and the sensed images are geometrically aligned so that final information is gained from the combination of various data sources. The determination of appropriate geometric transformation parameters is the key to the image registration process. In contrast, image registration or image alignment algorithm can be categorized into two. 1) Area-based methods, and 2) Feature-based methods. In area based method pixel intensity of corresponding region is a measure of similarity. Feature-based method use points, curves, lines, branches, and regions. This method establish a correspondence between a number distinct points in images.

Feature-based method has four steps-feature extraction, feature matching, transformation estimation, and image resampling. . Due to the large image size with local distortion satellite image registration uses feature based methods. The critical aspect of feature-based methods is to adopt discriminative and robust feature descriptors that are invariant to the assumed differences between the two input images, so that the extraction of invariant features is very important to registration results.

Recently, a scale-invariant feature transform (SIFT) [2] presented by David Lowe was applied to satellite images for extracting distinctive invariant features from images [3]–[6]. However, SIFT-based methods suffer from high complexity when extracting features points and computing descriptors. It also has drawbacks such as lack of feature points and distribution quality which will affect the registration accuracy.

High-resolution satellite images also contain local distortions due to different sensors having different paths, angles, and terrain relief, i.e., the number of feature points and distribution quality affect the accuracy. In general, corresponding feature points should be distributed throughout the image. To achieve robust registration of remote sensing images, we propose an automatic registration method based on modified Scale Invarient Feature Transform (SIFT) features. Also an efficient outlier detection method is proposed which is based on the consistency of dominant orientation of feature points.

II. Adaptive block processing and modified sift algorithm

A. Adaptive Block Processing

Block-based methods [6] have been applied to complex satellite images using SIFT. Nonblock-based methods

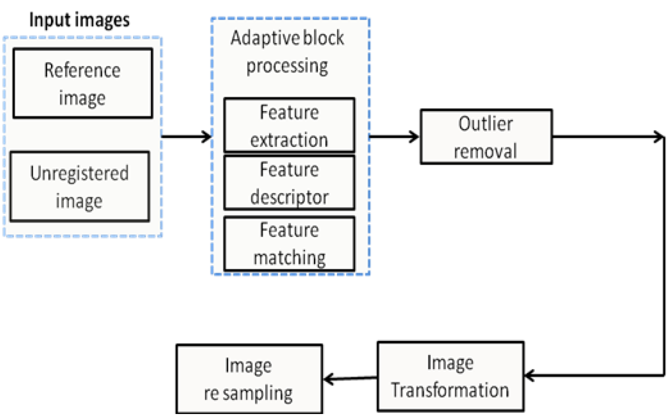

Fig 1: Flowchart of Proposed Algorithm

having a small image size, are typically inefficient in remote sensing, as the complexity of satellite images has increased due to increases in high-resolution imaging, and thus contain a greater amount of information. To overcome this problem, block-based methods for large image size have been proposed that the entire image X×Y is divided into smaller blocks M×N such that

$$IB(x,y) = \left\{(\xi,\zeta) \,\middle|\, |\xi\_x| \le \frac{M}{2} \wedge |\zeta - y| \le \frac{N}{2}\right\} \quad (1)$$

where denotes a pixel within the image block M × N . The major concern of these block-based methods is the need to reduce the processing time, and there is less concern about the number of features and their distribution quality.

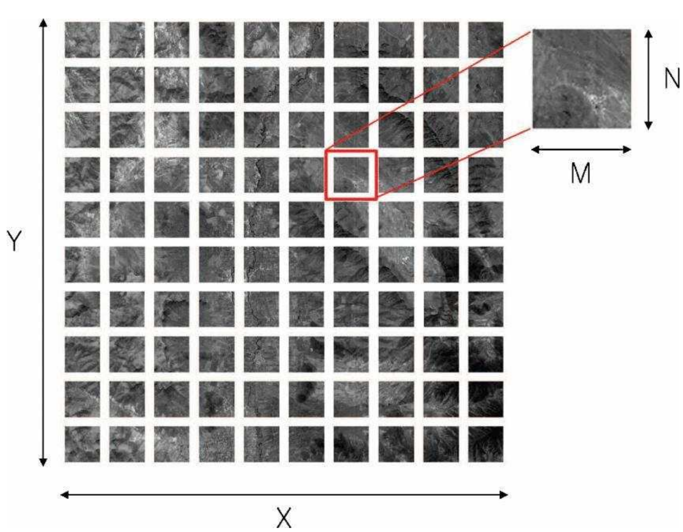

Fig 2: Block processing of satellite image

B. SIFT Algorithm

SIFT algorithm was proposed in [2] as a method to extract and describe key-points, which are robust to scale, rotation and change in illumination. SIFT bundles a feature detector and a feature descriptor. The detector extracts from an image a number of frames in a way which is consistent with variations of the illumination, view point and other viewing conditions. SIFT descriptor extracts from an image a collection of frames or key-points. There are five steps to implement the SIFT algorithm:

1. Scale-space extrema detection: Using a Difference of Gaussian (DoG) function the first stage searches over scale space to identify potential interest points that are invariant to scale and orientation.
2. Key-point localization: Based on measures of stability the location and the scale of each candidate point are determined and the key-points are selected.
3. Orientation assignment: Based on local image gradient directions one or more orientations are assigned to each key-point location.
4. Key-point descriptor: By computing the gradient magnitude and orientation at each image sample point in a region around the key-point location a feature descriptor is created. These samples are then accumulated into orientation histograms summarizing the contents over 4*4 regions with 8 orientation bins. So each key-point has a 128-element feature.
5. The correspondence of feature points can be determined by taking the ratio of distance for the descriptor vector from the closest neighbor to the distance of the second closest. Matching points are obtained using the NNDR [7], which uses the threshold in the ratio between the first and the second nearest neighbor descriptors. The NNDR can be defined as

$$NNDR = \left\| \frac{descr_A - descr_B}{descr_A - descr_C} \right\| \quad (2)$$

where and are the distances to the nearest and second nearest neighbors, respectively. is the base descriptor, and and are its closet two neighbors.

In our algorithm, the step 3) and 5) of the SIFT algorithm are modified, which will be used to extract features from the obtained images at each layer of the decomposition.

c. Modified SIFT Algorithm

The step 3 and 5 are modified inorder to get the new SIFT algorithm. In step 3), we propose to use the Prewitt operators on each keypoint. The computation of the gradient and the orientation computation are:

$$P_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}, \quad P_y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$dx(x,y) = P_x * L(x,y), \quad dy(x,y) = P_y * L(x,y)$$
$$m(x,y) = \sqrt{(dx(x,y))^2 + (dy(x,y))^2} \quad (3)$$
$$\theta(x,y) = tan^{-1}\left(\frac{dy(x,y)}{dx(x,y)}\right)$$

$$\theta'(x,y) = \begin{cases} \theta(x,y), & \theta(x,y) \in [0,180] \\ 360 - \theta(x,y), & \theta(x,y) \in (180,360) \end{cases} \quad (5)$$

In step 5), a new similarity measure is proposed. Firstly, a rough correspondence between key-points by using the step 5) of the SIFT algorithm is estimated. Assume that the two rough correspondence point sets are B= and C= where for each key-point and its corresponding point , , denotes the scale and orientation of and , and expresses the scale ratio and the orientation difference between them. Then, the scale ratio histogram and the orientation difference histogram are formed. The highest peaks in the two histograms correspond to the estimated value of scale ratio *s* and orientation difference θ, respectively. Assume that are two correlation windows of size (2w+1) x (2w+1) centered on and , represented as :

$$A_i^{uv} = I(x_i + su\cos\theta + sv\sin\theta, y_i + sv\cos\theta - su\sin\theta)$$
$$B_j^{uv} = x_j + u, y_j + v \quad (6)$$

Where u,v , is the element of centered on and is the element of centered on .

Finally, the new simillarity measure between key-points and can be represented as follows:

$$D(i,j) = \frac{c_{ij}+1}{2}\left[\left(1+\Delta_s(i,j)\right)\left(1+\Delta_\theta(i,j)\right).r(i,j)\right]^{-1} \quad (7)$$

III. Outlier removal using consistency of dominant orientation of feature points

Outlier detection is an important step in many computer vision and image analysis applications. The outliers are false matches of features that do not correspond to the same location in the real scene. The outlier detection methods usually utilize robust estimators and some constraints to find the outliers. The RANSAC (RANdom SAmple Consensus) algorithm [8] is a simple but powerful algorithm has been applied to initial correspondence sets to estimate the homography for outlier removal. In this paper we propose a fast and effective outlier detection method for matching multispectral and panchromatic images images. Our method employs a hypothesis test on the consistency of dominant orientations [9] of the feature points.

The main idea of the outlier detection methods is to check the matches against a constraint. The matches that are consistent with the constraint are taken as good matches while the matches that violate the constraint are rejected as outliers.

The steps of the proposed outlier detection method using orientation consistency test are described as follows:

Step 1: From the match set M randomly draw 8 matches.

Step 2: Let the differences of the dominant orientation between two features in each match be $\varphi_i(1,2,\ldots,8)$. Accumulate φ_i to an array R with length of 36.Each element in R represents 10 degree of rotation angle.If the value of φ_i falls into the orientation represente by R_i, then $R_i = R_i$+1 and $S_i = S_i + 1$. S in array with the same length of R and S corresponds to the accumulated rotation angle in R_i .

Step 3: Calculate sums of every three neighboring elements in R. Select the max value as $R_{sum\ -max}$. If $R_{sum\ max} < N_t$, then go for step 1.Here N_t is the empirical parameter. Otherwise let $\varphi_{aver} = S_{sum-max}/R_{sum-max}$. $S_{sum-max}$ is defined as the sum of three neighboring elements in S corresponding to $R_{sum\ -max}$.

Step 4: Step 4: For each match, compute the dominant orientation θ_k . If $|\theta_k - \varphi_{aver}| < threshold$, it is taken as one match

IV. experimental results

A. Accuracy Comparison

The root mean square error (RMSE) is a metric used to describe the accuracy of a registration process by measuring the location error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left\|p_i - \hat{p}_i\right\|^2}$$

where n is the number of points, are points in the reference images, and are estimated points in the transformation model.

B.

The experiments are carried out on panchromatic and multispectral the images. The proposed outlier method is evaluated with the RANSAC method. The result shows that our method is faster than the RANSAC method. For each method we perform the outlier detection for 100 times and calculate the averages. The terminated condition is that the maximum number of inliers is larger than 60

V. conclusion

In this paper, we introduced an adaptive block processing with improved Sift algorithm and to improve accuracy using a geostatistical analysis. The modified SIFT algorithm results in reduced number of descriptors. In addition, we also proposed an outlier removal algorithm based on the consistency of dominant orientation of feature points. This method can also identify the outliers that cannot be found by existing methods to provide results with better quality.

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