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FEATURE-BASED REMOTE-SENSING IMAGE REGISTRATION USING SIFT AND OPTIMAL RANSAC FOR OUTLIERS

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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). 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 Scale Invariant Feature Transform (SIFT) features, which can deal with the large variations of scale, rotation and illumination of the images.An outlier removal method called optimal RANSAC, which is an improvement of RANSAC is proposed; since standard RANSAC does not try to find the optimal set of inliers, instead it stops when the probability of finding more inliers reaches its predefined threshold. The consequence isthat it does not perform well for highly contaminated sets, i.e. when the set of outliers is large, since consensus might not be reached within reasonable time.

Keywords: Image registration; SIFT; RANSAC Optimal RANSAC

I. INTRODUCTION

Image registration [1] is a challenging task, which has wide applications in surveillance, motion estimation, and fusion systems. It is required in remote sensing applications for multispectral classification, change detection, image mosaicking, 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 [2]. 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 establishes a correspondence between number distinct points in images.

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. Feature-based matching methods are typically applied when the local structural information is more significant than the information carried by the image intensities. A high-resolution satellite image can be several hundred megapixels in size and occupy several spectral bands. Due to the limited resources such as storage and memory it is not efficient to process the entire image, even though high-resolution images provide detailed information. The number of feature points and distribution quality affect the accuracy. So we are going for an accurate image registration employing adaptive block processing for determining and efficient block size and an outlier removal method for finding the false matches. Even though there are different algorithms such as SIFT, SURF, PCA-SIFT [3]for image registration; SIFT algorithm developed by David Lowe is used for remote sensing image registration since others have low accuracy.
The objective of this work is to propose an efficient algorithm for removing the false matches and hence to register the images more efficiently. This algorithm is expected to find the optimal set for heavily contaminated sets, even for a lower inlier ratio. So we are going for an accurate image registration employing adaptive block processing based on semivaraince [4] for determining and efficient block size and an outlier removal called optimal RANSAC which is a modification of RANSAC for finding the false matches.

III. SYSTEM DESCRIPTION

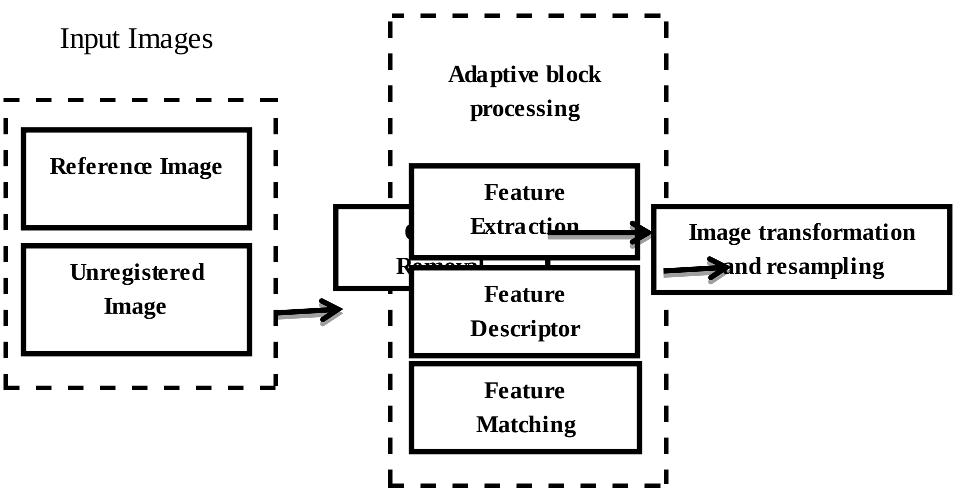

Fig 1: Flowchart of Proposed Algorithm

a. Input Images

Image registration is the process of aligning two or more images of the same scene taken at different times or different angles or from different sensors. Image registration is performed between two images having different contents and parameters, but having some common factors. Here the registration is performed with images taken from two sensors. Panchromatic image and multispectral images are used as inputs; both of them may be of the same area containing different features. Panchromatic image is considered as reference image and multispectral image as unregistered image.

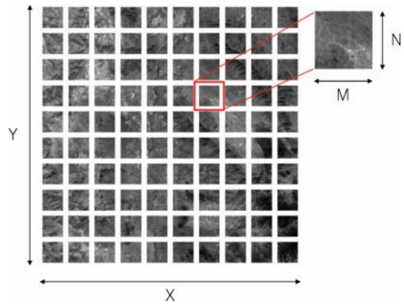

Fig 2: Block processing of satellite image

b. Adaptive block processing

The image is first subdivided into a number of blocks and each block is considered as individual image and is processed individually. Block size can be dynamic or predefined. If we are selecting the block size to predefined value there is a chance of unbalanced division of image, blocks without feature points and lesser number of feature points. So block size should depend on the nature of the content in the image. Here we are selecting the block size dynamically. For selecting the block size according to the image we are using semi-variance. Adaptive block processing means the block size is determined based on the number of matching points i.e. taking the block size with maximum number of matching features.

Semi-variance:Semi-variance is used to find the appropriate block size for processing the image. Block size varies according to the contents in the image. If the content of the image varies rapidly, the image should have smaller block size and if its contents are more uniform across image then it should have larger blocks. Semi-variance is calculated as the difference in value of pixels across the image.

Semi-variance is calculated for a possible set of block sizes and which block size returns the maximum value for semi-variance is selected as the block size.

c. Feature extraction and matching using SIFT Algorithm

Features are common but distinctive objects such as edges, curves, lines etc in an image. For registering two images these feature points in each image are extracted and are matched. In this process invalid features are eliminated in the process called outlier removal and then valid feature points are matched between the images. For matching purpose descriptor is created for each feature points and these descriptors are matched instead of directly matching the points.

Feature extraction: In the first step of feature extraction the image is represented in 3 different scale spaces. In this image is handled in different scales by representing an image as one parameter family of smoothened images parameterized by size of the smoothening kernel.

Difference of Gaussian of an image is calculated as the difference between the original image and Gaussian blurred version of same image which is in a different scale space.

$$D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma) \quad (1)$$

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \quad (2)$$

$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{\{-(x^2+y^2)/2\sigma^2\}}$(3)

Difference-of-Gaussian images are taken from adjacent Gaussian-blurred images. Once DoG images have been obtained, key points are identified as local minima or maxima of the DoG images across scales. This is done by comparing each pixel in the DoG images to its eight neighbors at the same scale and nine corresponding neighboring pixels in each of the neighboring scales. If the pixel value is the maximum or minimum among all compared pixels, it is selected as a candidate key point.

Feature descriptor: For a given feature point we describe the feature point in a 128- dimensional neighborhood. This descriptor describes the magnitude and orientation of the corresponding pixel. Each descriptor having a 4 × 4 grid in with each cell containing 8 orientations.

$$m(x,y) = \sqrt{\left(L(x+1,y) - L(x-1,y)\right)^2 + \left(L(x,y+1) - L(x,y-1)\right)^2} \quad (4)$$

$$\theta(x,y) = tan^{-1}\left(\left(L(x,y+1) - L(x,y-1)\right) \big/ \left(L(x+1,y) - L(x-1,y)\right)\right) (5)$$

Feature matching: Nearest neighborhood distance ratio is used for matching the feature points. It is the ratio of the distance with first and second nearest feature points. If the ratio is more than a cut off the feature points is considered as matched.

d. Outlier removal using Optimal RANSAC

In remote-sensing image registration based on feature matching, RANSAC [6] is used to determine which points are matching, so called inliers, and which points are false matches, so called outliers. The main disadvantage with standard RANSAC is that it is not repeatable since it is based on random sampling, as the name itself suggests: RANdom SAmple Consensus. Therefore, it is difficult using RANSAC while trying to run tests of other parameters involved in the application, as the set of inliers for the same pair of images may vary in each run. For satellite applications such as the one described later it is important that the result does not differ if the application is run more than once. Furthermore, standard RANSAC does not try to find the optimal set of inliers, instead it stops when the probability of finding more inliers reaches its predefined threshold. Due to its random nature, standard RANSAC is not always able to find the optimal set even for moderately contaminated sets and it usually performs badly when the number of inliers is less than 50%. Due to this reason standard RANSAC becomes less efficient in case of medical image and satellite image transformations. So we use Optimal RANSAC [7] instead of standard RANAC to find the inliers and outliers in an image. This algorithm is capable of finding the optimal set for heavily contaminated sets, even for an inlier ratio under 5%. The proposed algorithm is based on several known methods, which we modify in a unique way and together they produce a result that is quite different from what each method can produce on its own. This algorithm can be used for such transformations that can be constructed by more than the minimal points required and matching of aerial images using the Direct Linear Transformation, which requires at least four points.

Optimal RANSAC Algorithm:

1. Find tentative inliers by the resample algorithm.

2. Prune the set to the final tolerance.
3. Stop when the set is equal to the previous set.
4. Handle the rare cases when one more inliers are found.

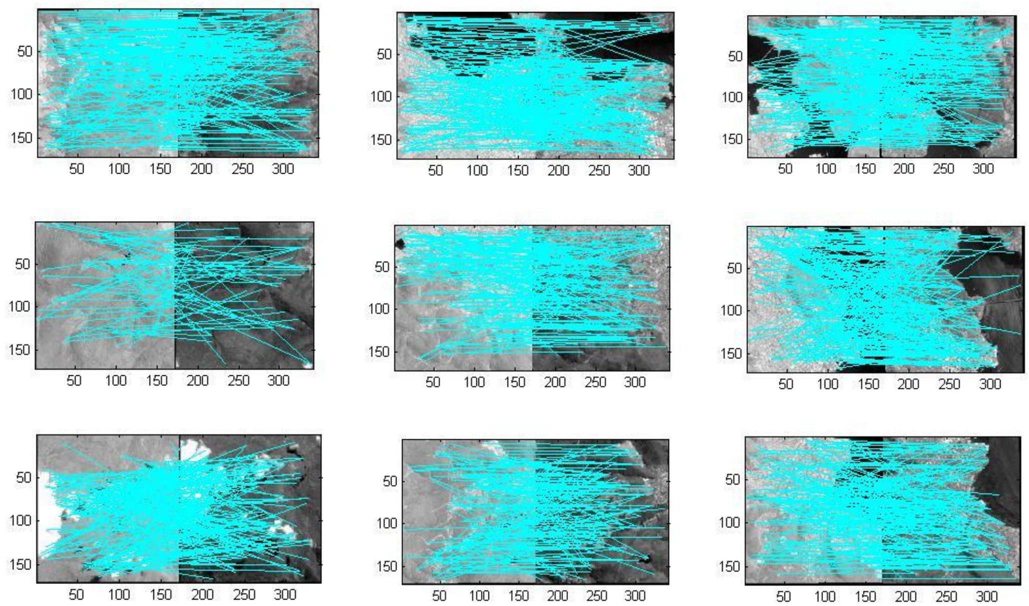

Fig 3: Showing the correspondence between matching points in both the images

III. RESULTS AND DISCUSSION

The registration method is implemented using MATLAB with i3 core processor; 2GB RAM. The input images taken for registration are panchromatic image as the reference image and multispectral image as the unregistered image. Both are the overview image of Hobart, Tasmania taken by IKONOS satellite. The spatial resolution of panchromatic image is 1m and that of multispectral image is 4m. The RMSE of the proposed method for a block size of 170*170 is 0.3710 as compared to that of RANSAC which is 0.6778.

Fig 4: Results of image registration: a) Reference image b) unregistered image c) image after registration d) & e) difference between registered and unregistered image

VI. CONCLUSION

In this paper, we introduced an adaptive block processing with Sift algorithm and to improve accuracy using a geo-statistical analysis. In addition, we also proposed an outlier removal algorithm based on

Optimal RANSAC which provides an optimal set of inliers even though the percentage of inliers is below 50%. Also from the experimental results, the RMSE of the proposed method is 0.3710 as compared to that of RANSAC which is 0.6778. We are setting the threshold for SIFT matching as 1.4 which will results in more number of feature points but also increased time . This can be reduced by utilizing a better feature matching algorithm.

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