Multi-Spectral Satellite Image Registration Using Scale-Restricted SURF

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***Abstract*—Satellites generally have arrays of sensors having different resolution and wavelength parameters. For some applications, images acquired from different viewpoints and positions are required to be aligned. This alignment process could be achieved by matching the image features followed by image registration. In this paper registration of multispectral satellite images using Speeded Up Robust Features (SURF) method is examined. The performance of SURF for registration of high resolution satellite images captured at different bands is evaluated. Scale restriction (SR) method, which has recently been proposed for SIFT, is adapted to SURF to improve multispectral image registration performance. Matching performance between different bands using SURF, U-SURF, SURF with SR and U-SURF with SR is tested and robustness of these with respect to orientation and scale is evaluated.**

Keywords- Image registration; image matching; satellite image processing

I. Introduction

Remote Imagery data is available in multiple bands. Each band captures a different wavelength range having different properties and used for specific purposes. For example some bands enable distinction of water areas while others are favored for detection of vegetation. For various applications, images acquired from different viewpoints and positions and at different bands are required to be aligned. This alignment process could be achieved by matching the image features followed by image registration.

Image registration is a key step in Remote Imagery. Commonly used image registration methods for multi-band images are region based [1], moment based [2], region and feature based [3] and FFT based [4] methods. Feature based image registration is generally composed of three steps: Extraction of image features and their descriptors, matching of these descriptors and forming relation between the images. Among feature based methods, moment based methods are more favorable [5]. Best known examples of moment based methods are Scale Invariant Feature Transform (SIFT) [6] and Speeded Up Robust Features (SURF) [7]. SURF is known to be several times faster than SIFT method. Also SURF is claimed to be more distinctive and repeatable [7].

In this paper we investigate the performance of SURF for the matching of high resolution multi spectral satellite images. We propose adapting the Scale Restriction (SR) method that has previously been used to improve SIFT method's matching performance to SURF. We evaluate the matching performance for SURF, Upright SURF (U-SURF) and also evaluate the performance of these methods when used the SR method is applied as a post-processing operation. In section 2, we describe the SURF algorithm. Then in section 3, we introduce the scale restriction method applied to SURF. Experimental results are presented in section 4 and concluding remarks are given in section 5.

II. Speeded Up Robust Features (SURF)

SURF is based on sums of 2-Dimensional Haar wavelet transforms and it uses integral images. Hessian Matrices are used to find features. SURF utilizes Haar wavelets to approximate determinant of Hessian blob detectors.

One of the main reasons of SURF's improved performance is the integral images [8] method. Integral Images are used to speed up calculation of any rectangular area. Given an input image I, integral image under point (x, y) is calculated by (1):

$$I_{\Sigma}(x, y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i, j) \quad (1)$$

Once the integral image is calculated for the input image I, calculating sum of intensities for a given pixel can be achieved by three additions. Cost of calculation is independent of image size, decreasing process time.

A. Hessian Matrix

SURF blob detector is based on determinant of Hessian matrix. Hessian matrix is used to detect

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location of blob like structures where determinant is maximum. For image point $I(x, y)$ the Hessian Matrix is defined by equation (2):

$$H(I(x,y)) = \begin{bmatrix} \frac{\partial^2 I}{\partial x^2} & \frac{\partial^2 I}{\partial y \partial x} \\ \frac{\partial^2 I}{\partial x \partial y} & \frac{\partial^2 I}{\partial y^2} \end{bmatrix} \quad (2)$$

The determinant of this matrix is calculated by (3):

$$det(H(I(x,y))) = \frac{\partial^2 I}{\partial x^2}\frac{\partial^2 I}{\partial y^2} - (\frac{\partial^2 I}{\partial x \partial y})^2 \quad (3)$$

The value of the determinant is used to classify maxima and minima of the function by second order test. Hessian Matrix for point $P(x, y)$ and scale σ is calculated as follows:

$$H(P,\sigma) = \begin{bmatrix} L_{xx}(P,\sigma) & L_{xy}(P,\sigma) \\ L_{xy}(P,\sigma) & L_{yy}(P,\sigma) \end{bmatrix} \quad (4)$$

where $L_{xx}(P, \sigma)$ is convolution of second order Gaussian derivative $\frac{\partial^2 g(\sigma)}{\partial x^2}$ for image point at $P(x, y)$ and similarly for L_{xy} and L_{yy}. These derivatives are known as Laplacian of Gaussians (LoG). SIFT approximates Laplacian of Gaussians (LoG) with Difference of Gaussians (DoG) [6], SURF method proposes approximation of Gaussian Kernels with box filters.

The proposed formula [7] for the approximation of determinant of the Hessian matrix is given by equation (5):

$$\det(H) \cong DxxDyy - (wDxy)^2 \quad (5)$$

w is calculated using energy conversion between Gaussian kernels and it is approximated as 0.9 by Bay *et al* [7].

B. Constructing Scale Space

Image pairs to be registered could have different scales and some image features could be found in different scales. In computer vision, scale spaces are constructed using pyramid images which are obtained by iteratively convolving original image with a Gaussian kernel and sub-sampling. This approach is successfully applied in SIFT [6] for the calculation of Difference of Gaussians.

SURF uses constant size box filters and due to use of these box filters it is not necessary to apply the same filter to the output of the previously applied filter layer. Instead of sub-sampling the image, filters are up-scaled resulting in an improvement of the performance; this is different to SIFT where images are scaled instead.

C. Orientation Assignment

In order to achieve rotation invariance, each interest point is assigned a reproducible orientation. Assume an interest point is found at scale s. Haar wavelet responses of $4s$ size are calculated for the neighboring pixels with radius of $6s$. Wavelet responses are weighted with a Gaussian ($\sigma = 2s$) and represented as points in space centered on interest point. Dominant orientation of responses is calculated with a sliding window of size of $\frac{\pi}{3}$. Longest orientation vector is selected as the dominant orientation and assigned to the descriptor.

U-SURF is the case of SURF that can be used when there is no or little rotation (up to 15°). U-SURF is faster to compute as it doesn't take the orientation information into account [7].

D. Descriptor Components

For an interest point centered around a point $P(x, y)$ and at scale s, the first task is to construct a square region of size $20s$. Each region is divided into 4 x 4 square sub-areas. Each sub area could be considered an area with 4 components. For each sub-area, Haar wavelet responses (size of $2s$) are computed at 5 x 5 regularly spaced samples. By denoting Haar wavelet responses for x and y components dx and dy, for 25 sample points sum of responses are calculated as:

$$v\text{sub} = \left[\sum dx, \sum dy, \sum |dx|, \sum |dy|\right] \quad (6)$$

III. SR-SURF

Scale Restriction method for SIFT (SR-SIFT) is reported to increase correct match ratio for satellite images where there is a constant scale difference [9,10]. In this work, Scale Restriction is adapted to SURF (SR-SURF).

When two images with constant scale ratio are matched, there is assumed an affine transformation between images. If there is an affine transformation, it means linear change for translation, rotation and scale between matched image key points. Scale Difference (SD) is defined for key point pair $P_1(x_1, y_1, \sigma_1, \theta_1)$ and $P_2(x_2, y_2, \sigma_2, \theta_2)$ as:

$$SD\ (P_1, P_2) = \sigma_1 - \sigma_2 \quad (7)$$

where x and y is location, σ is scale, θ is rotation of key point. Scale Restriction accepts matches within W scale difference to each other and rejects the ones outside this range (equation (8)).

$$\overline{SD} - W < SD < \overline{SD} + W \quad (8)$$

W has been reported to be found as 1.5 for SIFT [9]. In our experiments, we have observed that scale difference of correct matches is clustered around a constant value, close to the scale difference of the images. Hence, we propose to assign $\overline{SD}$ to the mean of the scale differences of all matches. Then we assign the standard deviation of scale differences to W. For example, for the scale difference histogram which is shown by Figure 1, $\overline{SD}$ is calculated as 1.8 and W is calculated as 0.81. Matches which have scale difference between $\overline{SD} - W$ and $\overline{SD} + W$ are accepted while the rest are ignored. This is expected to reduce the number of false matches while not having a significant effect on true matches.

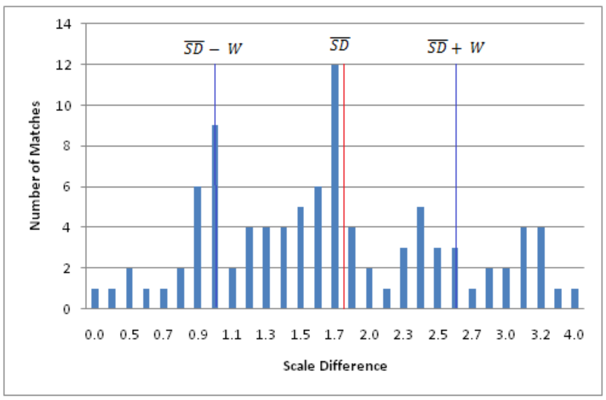

Figure 1. Scale Difference Histogram of Matches for NIR and Red image patches.

IV. EXPERIMENTAL RESULTS

First step to improve the correct match rate of SURF method is to apply a pre-processing step. Two methods have been compared for this purpose: contrast stretching and histogram equalization. According to our results, Histogram equalization is observed to be more effective and used as the preferred pre-processing method for the remaining of the experiments.

We used percentage of correct matches, P, over all the matches to compare the matching performance of the different methods. P is defined as ratio of correct matches, T_{CM} to total matches T_M:

$$P = 100 \times T_{CM} / T_M \quad (9)$$

If matches are within a neighborhood of each other for 2 pixels they are considered as correct matches. 35 test images of size 500x500 have been obtained from a 2500x3500 QuickBird image. Each 500x500-pixel image patch is processed by the test algorithms.

A. Tests without Rotation and Scaling

In this section, results of SURF, U-SURF, SR-SURF and U-SURF with SR tests will be given. Test images have the same scale and same orientation. NIR band images are used as the reference image set.

Table 1 shows average tests results of 35 QuickBird images. SURF method has a good performance ratio on bands which are closer to NIR, on the other hand NIR and Blue match ratios are low compared to other bands. SR increases P for all bands both when applied to SURF and U-SURF. Figure 2 shows the tests results as a chart for easier visualization.

For no rotation or slight rotation (+/- 15°) case, U-SURF could be applied. In our tests U-SURF performed better than SURF for no or slight rotation.

TABLE I. AVERAGE TEST RESULTS FOR 35 QUICKBIRD IMAGES. BLUE, GREEN, RED AND PANCHROMATIC BANDS ARE REGISTERED WITH NIR BAND.

		SURF	SURF with SR	U-SURF	U-SURF with SR
NIR – Blue	T_M	132.17	122.6	165.54	148.4
	T_{CM}	102.2	100.26	132.14	126.17
	P	77.32	81.78	79.82	85.02
NIR – Green	T_M	176.43	164.06	210.69	188.94
	T_{CM}	144.17	141.23	177.09	167.94
	P	81.72	86.08	84.05	88.89
NIR – Red	T_M	177.86	163.34	208.43	187.69
	T_{CM}	145.23	140.97	173.66	165.63
	P	81.65	86.3	83.32	88.25
NIR – Pan	T_M	354.51	326.63	380.14	342.8
	T_{CM}	306.2	295.86	331.11	312.51
	P	86.37	90.58	87.1	91.17

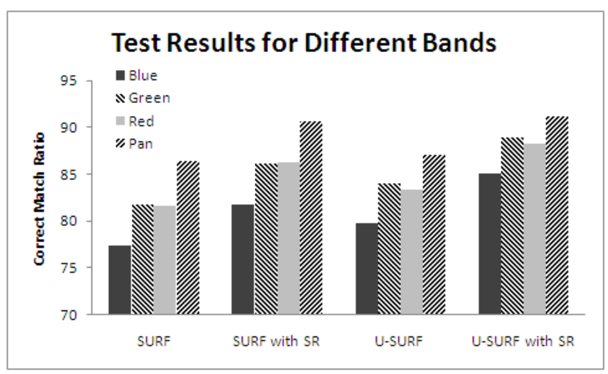

Figure 2. Average Test Results for of 35 QuickBird images.

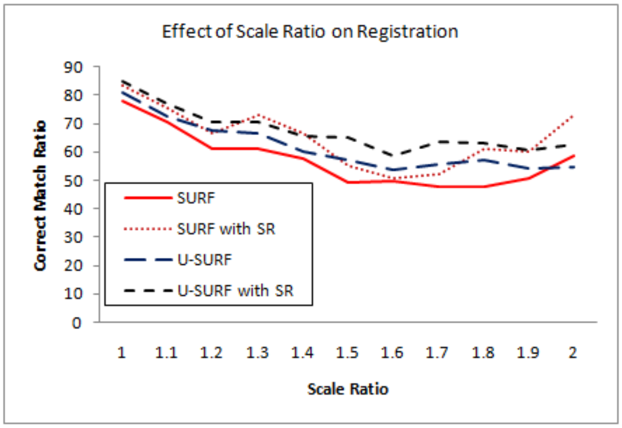

Figure 3. Scaling Test Results for QuickBird Image Patches for NIR and Red Bands.

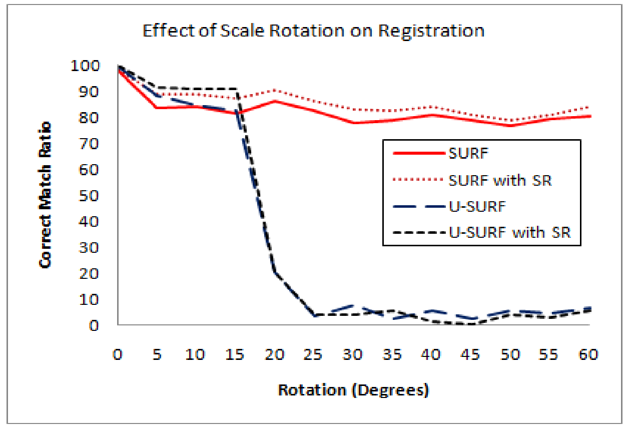

Figure 4. Rotation Test Results for QuickBird Image Patches for NIR and Red Bands.

B. Rotation and Scaling Tests

In this section SURF, U-SURF, SURF with SR and U-SURF with SR tests will be given for rotation and scaling. Same image patch from NIR and Red bands are used for testing. While NIR band images are used as reference, Red band image is scaled and rotated.

Scaling test results are given in Figure 3 for all four methods. As the scaling affects image resolution, T_M, T_{CM} and P decrease while scale ratio between images increases. SR method has been observed to increase correct match ratio for all scales by 1-10% both for SURF and U-SURF. Hence it is robust to scaling.

Rotation tests have been held by rotating one of the test images from 0° to 60° while keeping the other the same without rotation. Rotation test results for NIR and Red bands are given in Figure 4. As the rotation increases, images are deformed and as a result correct match ratio decreases for all the methods. SR increases the correct match ratio for both SURF and U-SURF methods. On the other hand, U-SURF performance decreases rapidly for orientations higher than 15°.

V. CONCLUSIONS

SR method has been shown to increase to correct matching rate while having little effect on the number of correct matches when there is a constant scale ratio between the images to be matched. It has been shown to be robust against scaling and rotation. According the experimental results, U-SURF with SR is the preferred method if there is no or little rotation. In the presence of rotation, U-SURF performance decreases rapidly and hence SURF with SR performs better.

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