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Image Registration of Satellite Images with Varying Illumination Level using HOG Descriptor based SURF

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Abstract

Image registration aligns two images geometrically, which is frequently required in medical, computer vision and remote-sensing field. It is a crucial pre-processing step in change detection or growth monitoring using satellite images. Accuracy of change detection depends on accuracy of image registration. For multi-modal, multi-sensor, multi-spectral satellite images one of the challenges for image registration is varying illumination level according to the sensor characteristics. This challenge is addressed by using Histogram of Oriented Gradient (HOG) along with Speeded-Up Robust Feature (SURF). It is shown that illumination variation gives some incorrect matches with SURF only which degrades image registration. Incorrect matches are reduced by using HOG as descriptor in SURF. Supporting simulation results for satellite images are presented which show the improvement in the correct matching rate.

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Keywords: image registration; SURF; HOG; satellite image; illumination variation; multi-spectral

1. Introduction

Image registration (IR) is the process of aligning two images-the target (or reference) image and the source (or sensed) image[1]. Basically IR determines the spatial or geometrical transformation that maps the points in the sensed image to the points in the reference image. IR is very crucial preprocessing step for the image analysis in which the

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final information is obtained from the combination of two images, such as remote sensing, computer vision and medical image analysis. In case of remote sensing applications, registration accuracy of less than 0.2 of a pixel is required to achieve a change detection error of less than 10%[15].

IR methods can be classified as Area (spatial or intensity) Based Methods (ABM) and Feature Based Methods (FBM) [1]. In ABM, intensity of every pixel in both images is used to compute some similarity metric (also known as cost function) to find the optimized geometric transformation iteratively. The computation time, especially for large satellite images, is more as every pixel is taken care of. In FBM, salient features of the images such as points, lines, edges etc. are detected and corresponded to find the required geometric transformation parameters. Relatively, this is faster and works well if salient features are available in the images as only those features are required to proceed further.

There are four steps in any FBM for IR: feature extraction, feature matching (using descriptor of the extracted features), geometric transformation estimation and re-sampling. In IR, depending on application, selection of feature extraction, its descriptor and matching method play important roles. The error in any of the steps of IR will be propagated in the next steps; accordingly it reduces the accuracy of IR.

During the last decade, Scale Invariant Feature Transform[2] (SIFT) and Speeded-Up Robust Features[3] (SURF) have been widely used for point feature extraction. SURF is derived from SIFT, but it is modified using hessian matrix, integral image and Haar response. This results in better performance and three time faster execution. Comparison of some of the feature extraction methods are also found[8,19].

SIFT is used in[4-7, 17, 20] for IR. In[17], for satellite images coarse IR is performed using SIFT to get its advantage of robustness and then fine IR is performed using mutual information to get its advantage of accuracy. Similarly in[21], coarse IR is performed using SURF and fine IR is performed using Harris corner detector. However this strategy of coarse-to-fine IR requires re-sampling process two times, so corresponding errors are added.

In our approach, SURF point features are used. Satellite images may be multi sensor, multi-spectral, multi-resolution or multi-temporal; they are typically large in size. Due to these characteristics of satellite images, conventional IR algorithms used for computer vision or medical images may face some problems. SURF is also giving incorrect matches, and hence improved in[9-12,21] for satellite IR. In[9] the normalized SURF algorithm can extract more accurate matching points than the original SURF algorithm; however the stability and robustness of the normalized SURF method still needs further study. In[10] feature points are extracted using SUSAN algorithm and they are described using SURF algorithm, where marginal improvement is found but results are not shown for challenging satellite images. In[11] performance of SURF for registration of high resolution satellite images captured at different bands is evaluated and then Scale Restriction (SR) method, which has been already proposed for SIFT, is adapted to SURF. In[12], SURF descriptor is modified according to the gradient reversals. This improves the Correct Match Rate (CMR) for multi-modal images but at the cost of reduced CMR for mono-modal images.

In SURF there are mainly three steps: point feature extraction, orientation assignment (optional step) and feature description. Our work is for feature descriptor. In SURF, Haar response based descriptor is used. Some alternatives for feature descriptors are compared in[13]. In[14], Histogram of Oriented Gradient (HOG) is used as feature descriptor for human detection. Because of its nature and as claimed by the authors it is illumination invariant. This is useful requirement for IR of satellite images with varying illumination level. To compare descriptor of SURF and HOG descriptor, around the same point two image patches are selected from the two images with different illumination level as shown in Fig. 1. For both the image patches, Haar based SURF descriptor vectors are plotted in Fig. 2 while HOG descriptor vectors are plotted in Fig. 3.This shows HOG descriptor is more illumination invariant compared to the descriptor of SURF.

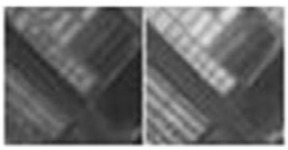

Fig. 1 Small low resolution image patches of size 41X41 pixel with different illumination level (increased in size for proper visual display purpose)

In our approach, the key idea is to use HOG as feature descriptor for SURF point features to address the illumination variation present between two satellite images. Such illumination variation may occur in certain cases such as multi-spectral images, multi-sensor satellite images.

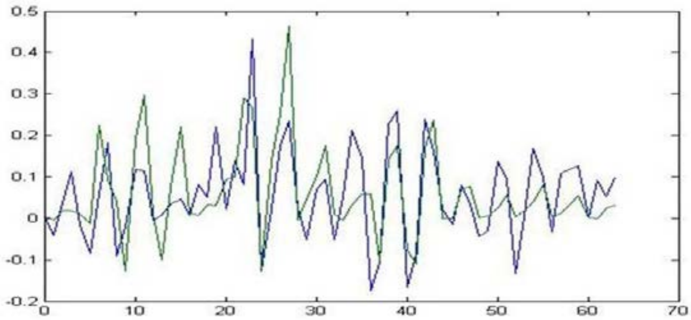
Fig. 2 SURF descriptor vectors of patches

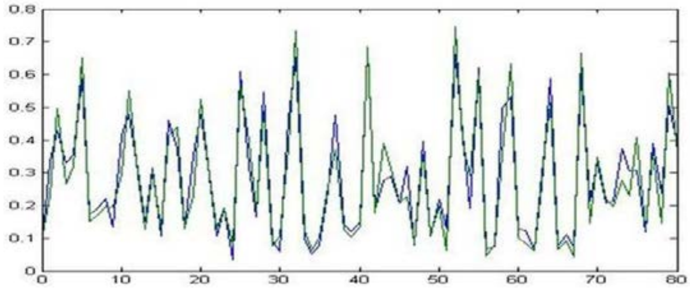
Fig. 3 HOG descriptor vectors of patches

In section II, related work of SURF and HOG is discussed in brief. Section III covers the proposed approach. Experiments and results are discussed in Section IV. Section V concludes the paper.

2. Related Work

2.1. SURF

SURF[3] is basically derived from SIFT with some improvements which are obtained by involving integral image, Haar wavelet response and approximation of hessian matrix. The most important characteristics of SURF is speed, simultaneously it has good performance of repeatability, distinctiveness and robustness. In general there are four steps in SURF: keypoint detection (also known as interest point or feature point), orientation assignment (optional step), local descriptor and keypoint matching (using its descriptor). Our work is related to the descriptor. In SURF, descriptor is generated in 20s square region around the keypoint. The region is divided into 4X4 square sub-regions. For each sub-region, Haar wavelet response in horizontal direction d_x and in vertical direction d_y are computed from 5X5 sample points. Finally, the responses and their absolute values are summed for each sub-region and accordingly 4-D descriptor vector (Σd_x, Σd_y, $\Sigma|d_x|$, $\Sigma|d_y|$) is formed. Combining this 4-D descriptor vector, for all 4X4 sub-regions resulted in a descriptor vector of length 64.

2.2. HOG

HOG descriptor is used in[14] for human detection. The essential thought behind the HOG is that local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions. The implementation of these descriptors can be achieved by dividing the image into small connected regions, called cells, and for each cell compiling a histogram of gradient directions for the pixel within the cell. The combination of these histograms then represents the descriptor. For improved performance the local histogram can be contrast-normalized by calculating a measure of the intensity across a larger partially overlapping region of the image. This normalization results in better invariance to changes in illumination or shadowing. In[14] for gradient computation, filtering is performed using the kernels, D_x = [-1 0 1] and D_y = $[1\ 0\ {-1}]^t$. Nine number of histogram channel is also suggested in their experiments.

3. Proposed Approach

In our approach, first optional step is to remove intensity difference between two images using their mean values. This step can't remove it completely as intensity levels are not necessarily related linearly in case of satellite images such as multi-spectral and multi-sensor images. Keypoints are extracted using SURF. Around every extracted keypoints, a 41X41 image patch as used in[13] is selected. For these image patches, corresponding HOG feature descriptors are computed. Number of bins selected in HOG, will decide the size of descriptor. The feature descriptor vectors are matched using Euclidean distance. The steps for proposed approach are shown in Fig. 4.

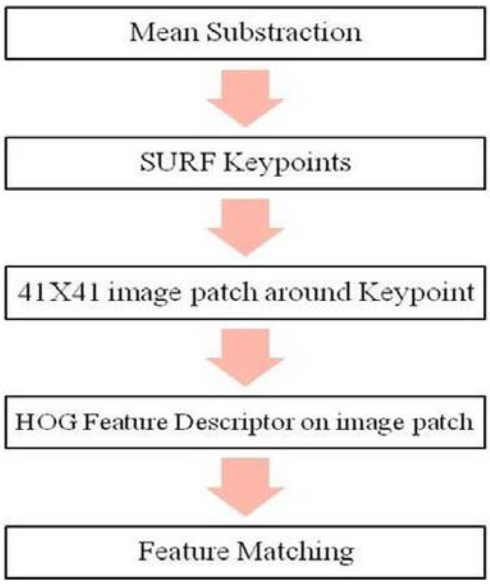

Fig.4 Steps for proposed approach

4. Experimental Results and Discussion

For performance parameter, as normally preferred, CMR is used. Further correct@N[12] is also used, because in IR first few best matched features are used to estimate the registration parameters based on the geometric transformation under consideration like rigid, affine etc. In our analysis N=20 is taken, same as in[12]. Implementation is in MATLAB, on Pentium Dual-Core CPU with 2 GHz and 2 GB RAM.

Two datasets of size 400X300 obtained from[17,18] and two more multi-spectral satellite image datasets from LISS-III sensor of size 1000X1000 obtained from Bhuvan portal of NRSC, ISRO[16] are shown respectively in first and second row of Fig. 5, which show large illumination variation. Best 20 matched feature points for Dataset-1 are shown in Fig. 6 for two approaches: Approach-A using SURF with its Haar based descriptor of 64 size called SURF-64, and Approach-B using HOG descriptor (with number of bins=9 i.e. descriptor size of 81 as it is suggested as best value[14]) with SURF called HOG-81. The Fig. 6 shows, for Approach-A, 10 matches are correct out of best 20 matches i.e. correct@N is 10, while for Approach-B, 15 matches are correct out of best 20 matches i.e. correct@N is 15. Similar observation for dataset-3 is shown in Fig. 7. Further analysis was also carried out for different bin size in

HOG. Comparable results are found in case of 7 numbers of bins i.e. HOG descriptor size is 63. For comparison purpose this is also included as approach-C called HOG-63.

For all four datasets, Fig. 8 shows the CMR while Fig. 9 shows the correct@N (N=20). This shows improved performance of using HOG as descriptor for satellite images. Computation time is not significantly changed as shown in table 1.

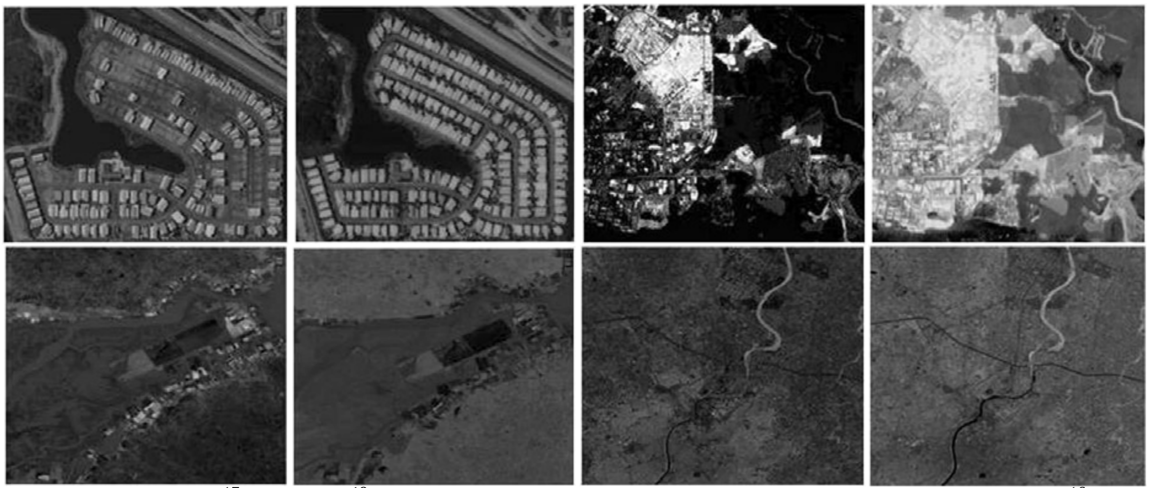

Fig. 5 Dataset-1[17], dataset-2 [18], dataset-3 (near bay of Kutch) and dataset-4 (near Ahmedabad city) [16]

a b

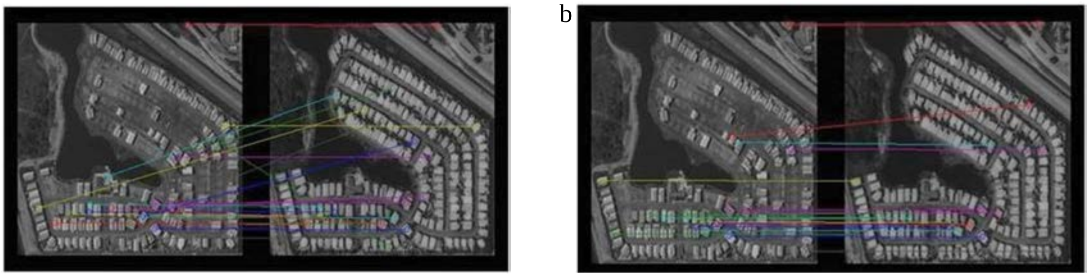

Fig. 6 Matched point features for dataset-1 using (a) Approach-A (b) Approach-B

a b

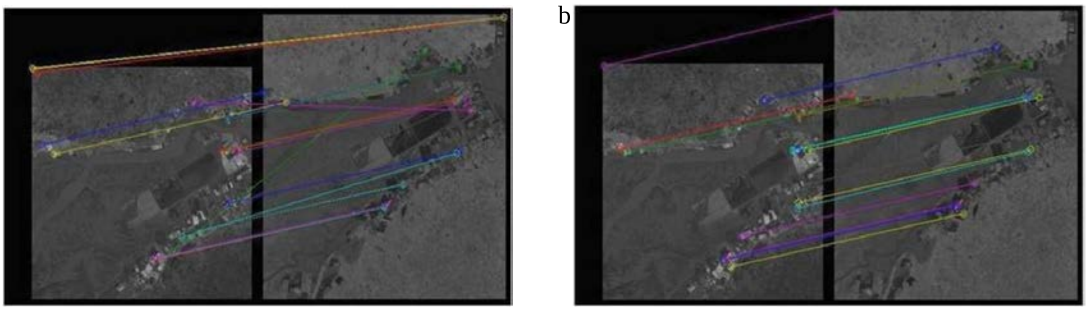

Fig. 7 Matched point features for dataset-3 using (a) Approach-A (b) Approach-B

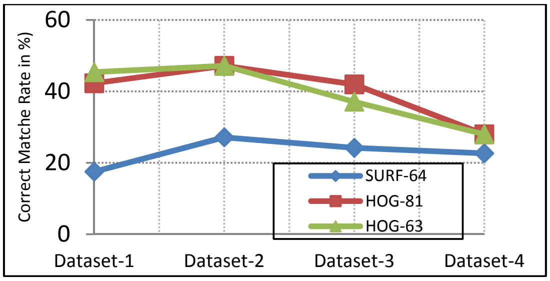

Fig. 8 CMR for all four datasets

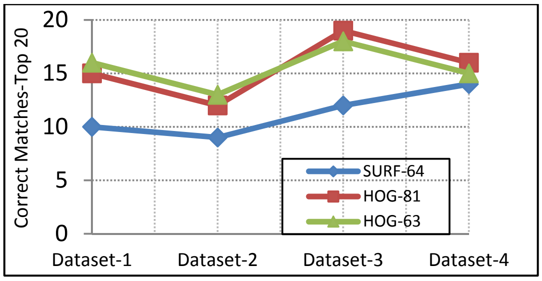

Fig. 9 Correct@N, N=20 for all four datasets

Table 1. Computation Time

	Computation Time in second			
Approach	Dataset-1	Dataset-2	Dataset-3	Dataset-4
SURF-64	3.33	2.63	13.80	15.28
HOG-81	3.18	2.37	13.52	16.19
HOG-63	3.14	2.32	13.62	15.30

For further analysis, images of a same scene captured by various sensors such as SPOT, Landsat, IRS and air photo are obtained from[22], which are having illumination variation as shown in Fig. 10. From these images with different combination, six image pairs are formed. For these pairs observed CMR using the SURF-64 and HOG-81 approaches are compared in Fig. 11. This shows the performance improvement in case of multi-sensor satellite images.

To observe the effect of improved CMR on IR, first of all incorrect matches i.e. outliers are removed from the initial few matches using RANSAC approach[23]. Then after, predefined numbers of correct matches are used to find the registration or transformation parameters. If ground truth is not available then it is difficult to compare the results. But for the known registration parameters the results can be compared. During various experiments, improved accuracy is observed in estimating registration parameters for the suggested approach. This improvement in IR is due to the improvement in CMR. For example the dataset-3 was translated in x-direction and y-direction by 100 pixels and 200 pixels respectively. The SURF-64 approach has estimated it as 100.90 and 200.6 pixels while HOG-81 approach has estimated it as 100.70 and 200.51. Similar improvement is also observed with small rotation as well.

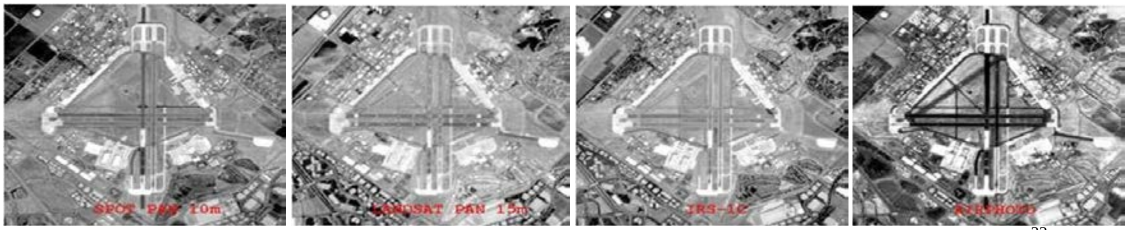

Fig. 10 Multi-sensor image dataset for the same scene: SPOT, Landsat, IRS and Air photo[22]

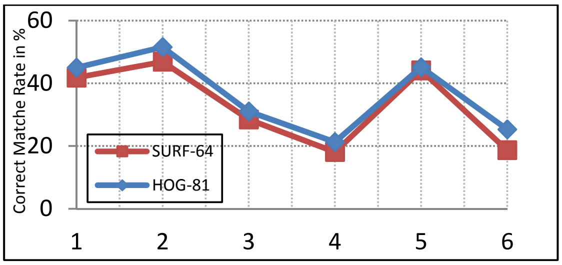

Fig. 11 CMR for six multi-sensor image pair datasets

5. Conclusion

Compared to SURF with Haar response based descriptor, SURF with HOG based descriptor is found more appropriate in case of images with illumination variation such as multi-spectral and multi-sensor satellite images. Good improvement is observed in correct@N value for HOG based SURF. For small rotation performance in terms of correct@N is comparable but large rotation degrades it. This large rotation will be addressed in future work. Further experiments will be carried out on more satellite image datasets.

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