Image Registration Algorithms for Satellite and Remote Sensing Applications

PhD Synopsis

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1. Abstract

Image Registration (IR) is the process of overlaying images of the same scene taken at different times, from different viewpoints, and/or by different sensors. It is a vital problem in the applications where the final information is based on the comparison of images, such as remote sensing, medical diagnosis, computer vision etc. The reason for the increased significance of IR for satellite images is that remote sensing is currently moving towards operational use in many important applications, both at social and scientific levels. The satellite images are multi-temporal (taken at different dates), multisource (derived from multiple sensors) or multimodal (obtained with different acquisition modalities). IR for remote sensing is also difficult due to the challenges such as large image size, having different intensity level, noise, clouds etc.

Broadly there are two approaches for IR: Area Based Methods (ABM) and Feature Based Methods (FBM). For ABM, choice of similarity measure is very important so IR using Mutual Information as a similarity measure is investigated as it is best suited for multimodal images; but the computational complexity is challenging. Transform domain properties of radon transform are used to find registration parameters.

In FBM there are four steps: feature detection, feature matching, estimation of registration parameters and re-sampling. Speeded up Robust Feature (SURF) is explored which is found little in literature for satellite IR. Direct use of SURF is not appropriate for many cases of satellite IR. Satellite IR with varying intensity level is improved using Histogram of Oriented Gradient (HOG) descriptor in SURF, as HOG descriptor is more illumination invariant. Further, if the images are having clouds or shadows, they lead to some false matches. The features related to clouds or shadows are removed using SVM classification, this results in reduction of false matches. It is shown that by both the modifications i.e. HOG as a descriptor and classification in matching step lead to improvement in CMR which ultimately improves the IR.

2. State of the art of the research topic

Image registration (IR) approaches can be classified as Area (spatial or intensity) Based Methods (ABM) and Feature Based Methods (FBM) [1].

Area Based Methods (ABM)

In ABM, intensity level of every pixel in both images is used to compute some similarity measure, iteratively to find the optimized geometric transformation. In ABM selection of similarity measure plays significant role. Various similarity measures such as Sum of Squared Difference (SSD), Sum of Absolute Difference (SAD), Cross Correlation (CC), Normalized CC, Mutual Information (MI) etc. are used to measure the similarity between the reference and sensed images [2], [3]. IR steps for ABM are shown in Fig 1.

For multimodal images due to illumination variation other similarity measure may fail but MI can be preferred. MI has been widely used in medical field [4]-[7] for IR, but for remote-sensing a little recent works is found [3]. Some of the similarity measures for remote-sensing are compared in [12] which show the superiority of MI. Optimization techniques and multi-resolution approaches are used to improve speed and accuracy of MI based IR for satellite images. Computational complexity of IR using MI is challenging as every pixel is taken care of.

Some methods also use transform domain and based on its properties, registration parameters are computed, so that they can be treated as transform domain based methods. Fourier transform properties are used to estimate the registration parameters in [13].

Feature Based Methods (FBM)

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 in most of the cases. But if the features are not easily identified from the images then the registration will not be accurate or may not work. General steps in FBM for IR are shown in Fig. 2.

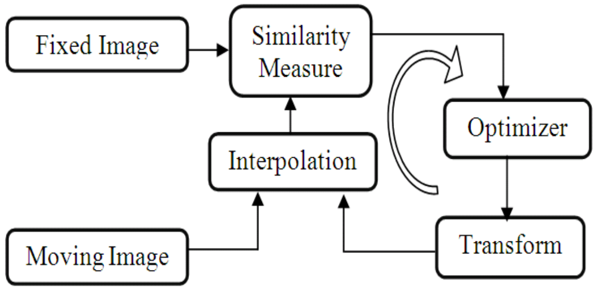

Fig. 1 IR steps in ABM [3]

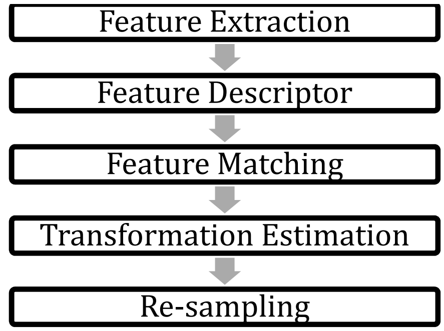

Fig. 2 IR steps in FBM [1]

During the last decade, Scale Invariant Feature Transform (SIFT) [16] and Speeded-Up Robust Features (SURF) [17] have been widely used for 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 times faster execution. Some of the feature extraction methods are compared in [22] and [23].

SIFT is used in [18]-[21], [24] for IR. In [24], 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 [25], 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.

Due to the characteristics of satellite images, conventional IR algorithms used for computer vision or medical images may face some problems. SURF is also giving false matches, and hence improved in [25]-[29] for satellite IR. In [26] the normalized SURF algorithm can extract more accurate matching points than the original SURF algorithm; however the stability and robustness of the normalized SURF matching algorithm still needs further study. In [27] feature points are extracted using SUSAN algorithm and they are described using SURF algorithm, but results are not shown for challenging satellite images. In [28] 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 [29], SURF descriptor is modified according to the gradient reversals. This improves the Correct Match Rate (CMR) for multimodal images but at the cost of reduced CMR for monomodal images. In general for FBM, improvement in any of the feature extraction, feature description and feature matching step leads to the improvement in IR.

From literature survey it is observed that using signal and image processing techniques in feature extraction, feature description or feature matching steps, some of the issues of satellite IR are addressed for the specific datasets.

3. Definition of the Problem

To propose an improved automatic IR algorithm for multi-spectral, multi-sensor, multi-temporal satellite images which are large in size, having intensity level variations and/or clouds or shadow.

4. Objectives

- To study and investigate area based methods and feature based methods of IR for satellite images and remote-sensing applications
- Using signal/image processing techniques, suggest an approach to address some of the challenges for satellite IR
- To address the intensity level variation issue for satellite IR, as it commonly occurs in case of multi-spectral, multi-modal, multi-temporal and multi-sensor cases.
- To address the issue of clouds/shadows in satellite images for IR, frequently present in many cases and affect the accuracy of the IR.

5. Scope of the work

- There is no unique algorithm for satellite IR which works for all kind of satellite images. So the suggested approach for IR can be used for presented kind of datasets before image fusion step; this is an essential pre-processing step in any image fusion process of many remote-sensing applications such as urban growth detection, effect of natural hazards, vegetation index etc.

6. Original contribution by the thesis

The original contribution of the thesis is in terms of modifications suggested in IR algorithms for satellite images. In SURF based FBM algorithm, use of HOG descriptor and use of classification of features before feature matching, both leads to improvement which is reported using CMR. The original contribution is also observed in the research papers listed at the end.

7. Methodologies of Research and Results

All the simulation work is carried out in MATLAB, on Pentium Dual-Core CPU with 2 GHz. Some of the datasets are collected from [31], [32], [33], including the Bhuvan portal.

ABM: MI as similarity measure

Some of methods for the estimation of MI have been surveyed and compared [34]. In [35] new method for the estimation of MI based on maximum likelihood is proposed which is called as MLMI. This MLMI method has several advantages such as it does not involve density estimation and directly models the density ratio,

$$w(x, y) = p_{xy}(x, y) / p_{xy}(x)\, p_y(y)$$

Thus it is a single-shot procedure without division by estimated quantities and therefore the estimation error is not further expanded and the unique global optimal solution can be obtained efficiently. We have investigated the use of MLMI method to estimate MI for images. And this estimated MI is used as a similarity measure in the IR process.

To perform IR process, one test image, say reference image is taken. Second rotated image, say sensed image is synthesized by applying small known arbitrary rotation. In IR process, this sensed image is required to be aligned with the reference image. To perform IR, the sensed image is rotated in step within predefined range of angle, and for every step of rotation MI with reference image is found. The maximum value of MI is found from all MI values. The angle corresponding to this maximum value of MI is the angle of rotation. So the sensed image is de-rotated by the same angle to align it with the reference image.

In the experiment, for ABM of IR, MI is estimated using two different methods-histogram based and MLMI. It is repeated for different images with different size including satellite images. For both methods and for different images, the processing time is summarized in Table I. It shows that processing time is less for IR using MLMI based MI as compared to the IR using histogram based MI, but the reliability is reduced. It is also observed that ABM is should be preferred if the initial solution is close to the final solution and degree of freedom is minimal, otherwise computation time is challenging. It can be used in fine IR stage in coarse-to-fine IR approach [24], [25].

TABLE I. COMPUTATION TIME FOR IMAGE REGISTRATION USING MLMI

Images	**Rotation applied to sensed image (degree)**	**Steps for Rotation (degree)**	**Computation Time for MLMI (second)**	**Computation Time for histogram based MI (second)**
image-1, 1024X1024	-4	-5 to 5	355	610
image-2, 512X512	2	-3 to 3	77	144
image-3, 2091X2018	2	-3 to 3	474	730
image-4, 512X512	-2	-3 to 3	109	141
image-5, 512X512	-4	-9 to 9	167	478
image-5, 512X512	-6	-8:8	94.2	176.5
image-5, 512X512	7	-9:9	105.7	226

Transform Domain: Radon Transform

Next literature review was done for transform based IR, where both images are first transformed to another domain and properties of that transform domain are utilized to find geometric transformation parameters i.e. rotation, scale, translation (RST) etc. One of best example using Fourier transform is in [13], where shifting property and log-polar mapping are used to find RST.

The Radon transform computes the projections of an image matrix along specified directions [36]. Mathematically, the radon transform is defined for a function f (x, y) as

$$R_f(r,\theta) = \int f(x,y)\,\delta\big(r - x\cos(\theta) + y\sin(\theta)\big)dxdy$$

$$= F^R(r,\theta)$$

$$x, y, r \in R \text{ and } \theta \in [0,\pi]$$

This equation can be interpreted as the integral of function $f(x,y)$ over the line

$$r = (x\cos(\theta) + y\sin(\theta))$$

Any translation in spatial domain leads to translation in the r direction of the radon domain. The amount of translation also varies with the theta dimension of radon transform. The scaling of the original image results in the scaling along the r axis in the radon domain. The value of the transform is also scaled. The rotation in spatial domain leads to circular translation along the theta axis in the radon domain. These properties of the Radon transform are summarized in Table II. As an example, the Fig. 3 explains the vertical translation property.

TABLE II. PROPERTIES OF RADON TRANSFORM

Image	**Input image *f***	**Radon Transform F^R**
Original	$f(x,y)$	$F^R(r,\theta)$
Translated	$f(x-x_o, y-y_o)$	$F^R(t-x_o\cos\theta - y_o\sin\theta, \theta)$
Scaled	$f(ax, ay)$	$\frac{1}{\lvert a\rvert}F^R(at,\theta)$
Rotated	$f(r, \emptyset+\theta_0)$	$g(t, (\emptyset+\theta_0, \mathrm{mod}\ 2\pi))$

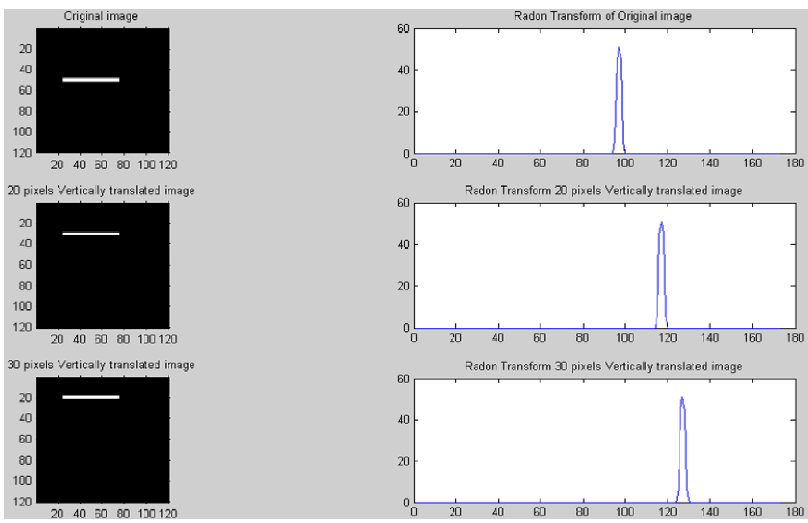

Fig.3 Effect of vertical translation is observed in radon domain

In our work, different amount of rotations and translations are applied to some images. Correspondingly different images with θ degree rotated, t_x pixels translated in the x direction and t_y pixels translated in the y direction have been synthesized. Between the synthesized images (geometrically transformed) and original image, the radon transform is applied. Using the properties discussed above θ**,** t_x and t_y have been estimated. The known actual values and the values estimated from simulation are summarized in Table-III. In most of the cases the estimated parameters values are very close to the actual values. This shows the accuracy and reliability of the approach. Computation time is also comparable as far as IR is considered. To observe the effect of noise on the performance, same steps have been repeated after adding various amounts of noise levels in the images. Good robustness against is noise is observed.

TABLE III. ACTUAL AND ESTIMATED Θ, T_X AND T_Y PARAMETERS & COMPUTATION TIME FOR VARIOUS IMAGES

Images	Actual Parameters			Estimated Parameters			Computation time (Second)
	$\boldsymbol{\theta}$ (degree)	$\boldsymbol{t_x}$ pixel)	$\boldsymbol{t_y}$(pixel)	$\boldsymbol{\theta'}$ (degree)	$\boldsymbol{t'_x}$(pixel)	$\boldsymbol{t'_y}$(pixel)	
image-1 489X300 125kb	0	20	35	0.5	20	27	4.3
	20	5	17	18.5	7	15	4.24
	10	35	17	10.5	34	17	4.38
	25	14	30	23.5	15	19	4.2
image-2 579X481 43.7kb	0	20	35	0.5	20	35	8.35
	20	5	17	20	4	18	7.78
	10	35	17	10	35	18	7.91
	25	14	30	25	14	31	7.73
image-3 3264X2448 467kb	0	20	35	0.5	16	37	223.52
	20	5	17	20.5	6	20	208.32
	10	35	17	10.5	13	18	214.3
	25	14	30	25.5	15	33	206.63
image-4 256X256 65kb	0	20	35	0.5	20	35	2.42
	20	5	17	18	5	16	2.20
	10	35	17	9.5	34	17	2.25
	25	14	30	24	13	29	2.19

FBM: use of HOG descriptor in SURF to address intensity variation

Based on results and learning experience from ABM, further scope of work is narrow down to the FBM only. As shown in Fig. 2, the steps in FBM: feature extraction, feature representation, feature matching, registration parameter estimation and re-sampling. In SURF there are mainly three steps: feature extraction, orientation assignment (optional step) and feature description. This work is for feature descriptor step of SURF. In SURF, haar response based descriptor is used. In [37], 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, two image patches around the same point are selected from the two images with different illumination level as shown in Fig. 4. For both the image patches, haar based SURF descriptor vectors are plotted in Fig. 5 while HOG descriptor vectors are plotted in Fig. 6. This shows that HOG descriptor is more illumination invariant compared to the descriptor of SURF.

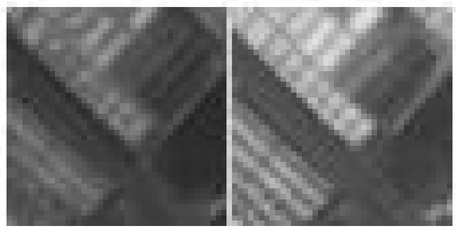

Fig.4 Image patches with different illumination level

Here, the idea is to use HOG as feature descriptor for SURF extracted keypoints 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.

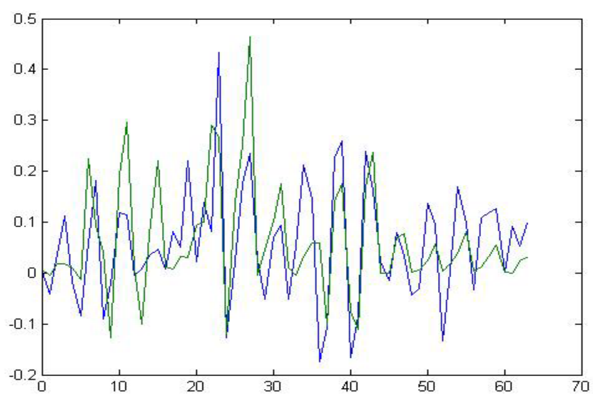

Fig.5 SURF descriptor vectors of patches

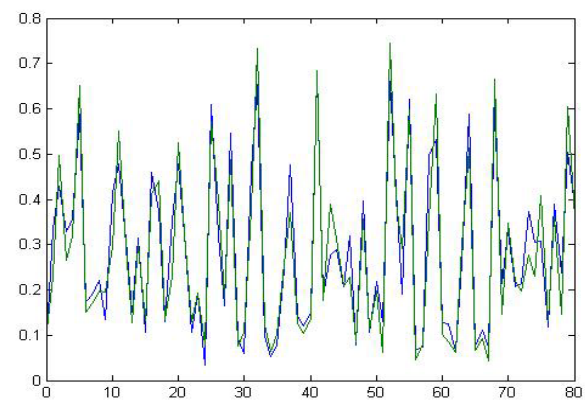

Fig.6 HOG descriptor vectors of patches

The steps for proposed approach are shown in Fig. 7. The first and optional preprocessing step is to remove intensity difference between two images using their mean value. This step can't remove it completely as intensity levels are not necessarily related linearly in case of satellite images. Keypoints or feature points are extracted using SURF. Around every extracted keypoint, a 41X41 image patch 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 extracted feature vectors are matched using Euclidean distance.

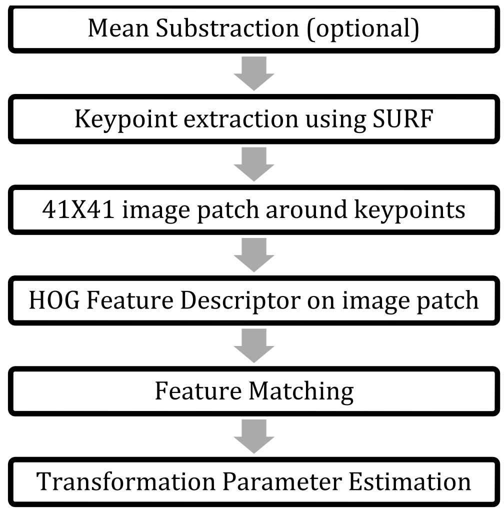

Fig.7 Steps for proposed approach

In FBM for IR, for performance parameter, as normally preferred, CMR is used. Further CMR for the first best 20 matches is also used [29], because in registration first few best matched features are used to estimate the registration parameters based on the geometric transformation under consideration like rigid, affine etc.

Two datasets obtained from [32], [33] and two more multi-spectral satellite image datasets of LISS-III sensor obtained from Bhuvan portal [31] are shown in Fig. 8, which show large illumination variation. Best 20 matched feature points for Dataset-1 are shown in Fig. 9 for two approaches: Approach-A using SURF with its haar based descriptor with size of 64 called SURF-64, and Approach-B using HOG descriptor (with number of bins=9 i.e. descriptor size of 81) with SURF called HOG-81. The Fig. 9 shows, for Approach-A, 10 matches are correct out of best 20 matches, while for Approach-B, 15 matches are correct out of best 20 matches. Similar observation for dataset-3 is shown in Fig. 10. Further analysis was also carried out for different bin size in HOG. Comparable results are found in case of seven 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. 11 shows the CMR while Fig. 12 shows the CMR for first best 20 matches. This shows improved performance of using HOG as descriptor for satellite images.

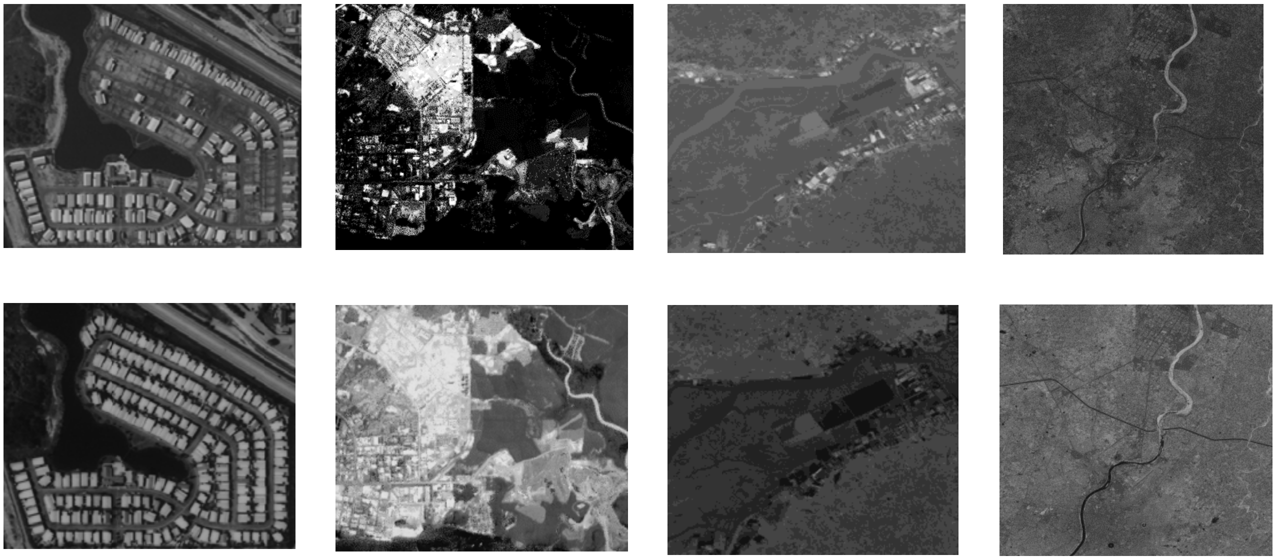

Fig. 8 Dataset-1 [32], dataset-2 [33], dataset-3 (near bay of kutch) and dataset-4 (near Ahmedabad city) [31]

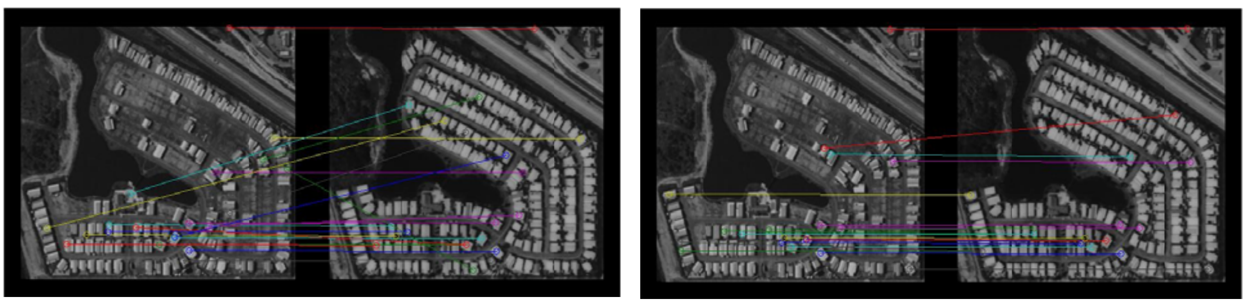

Fig. 9 Matched features for dataset-1 using (a) Approach-A (b) Approach-B

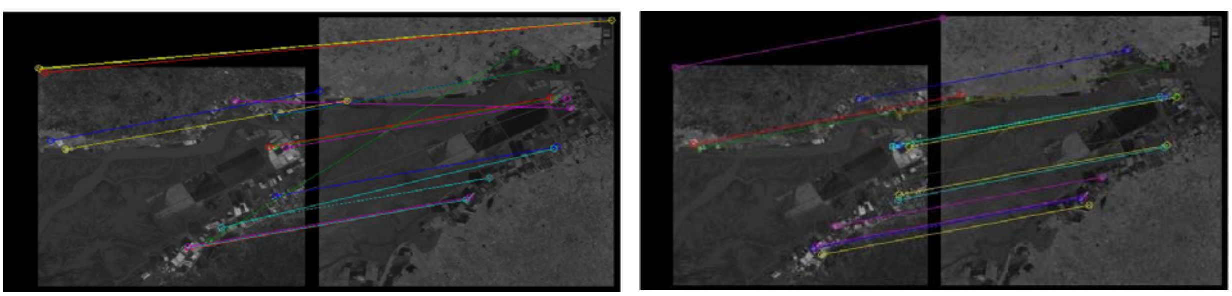

Fig. 10 Matched features for dataset-3 using (a) Approach-A (b) Approach-B

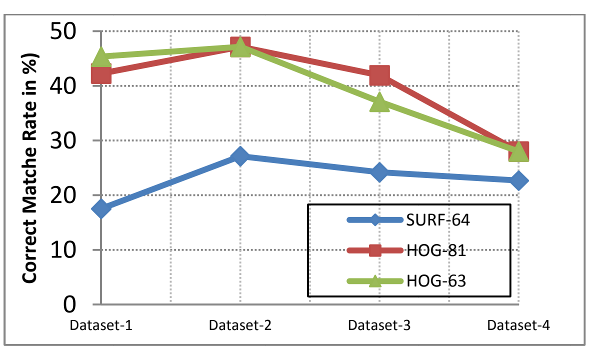

Fig. 11 CMR for all four datasets

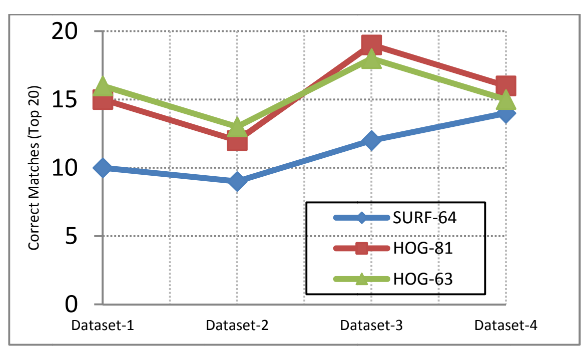

Fig. 12 CMR for first best 20 matches

FBM: use of classification in matching step to address clouds

Further the work is done in feature matching step. In this work CMR is improved for the case of having some clouds or shadows in satellite images. For example if clouds are present in the images then the matched features corresponding to them are not useful. In case of multi-temporal images if the clouds are shifted in second image then they may be correctly matched but give wrong registration parameters. So it is better if the feature points related the cloudy areas are removed before the matching step. This will reduce the false matches and so improves the CMR. This is achieved by SVM based classification of the features. The steps are shown in Fig. 13

For one of the image pairs the result is shown in Fig. 14 where, so many false matches related to cloudy areas are observed, many of them are removed after SVM classification. The classification of cloudy and non-cloudy features points are also observed in the scatter diagram shown in Fig.15. The CMR is significantly improved from 6.7% to 20.8%. For some other simulation results the improvement in CMR is from 19.56% to 34.04%, 15.22% to 40% and so on.

The performance of the suggested modification highly depends on the training of the SVM for the classification. For this purpose image patches around the extracted point are used. Among them, very carefully chosen some cloudy and non-cloudy image patches are used for training purpose.

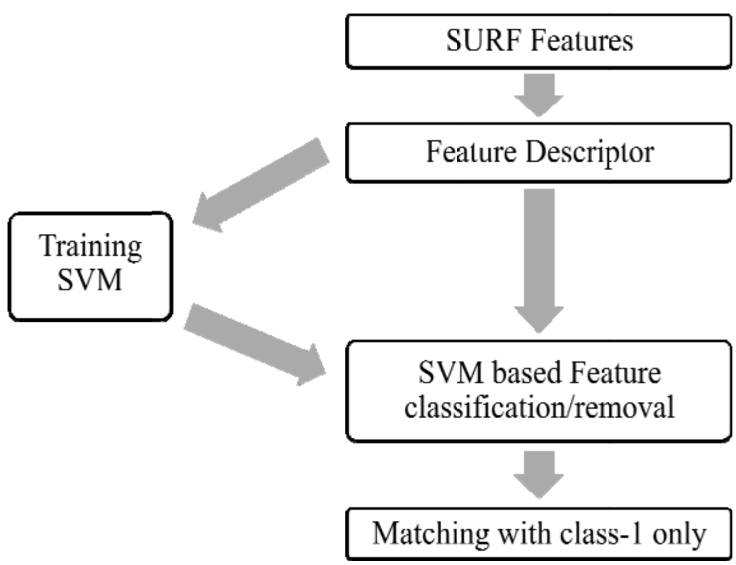

Fig. 13 Steps with modification using classification in matching step

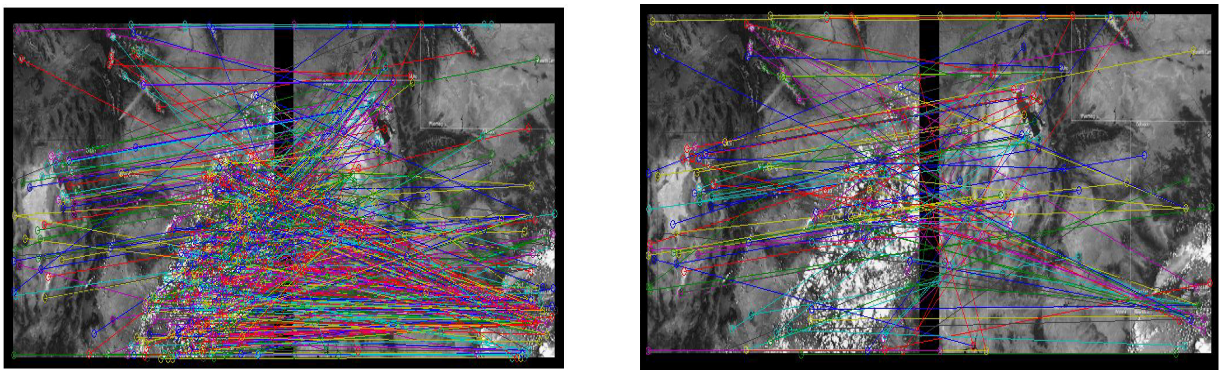

Fig. 14 Matched key-points before and after classification

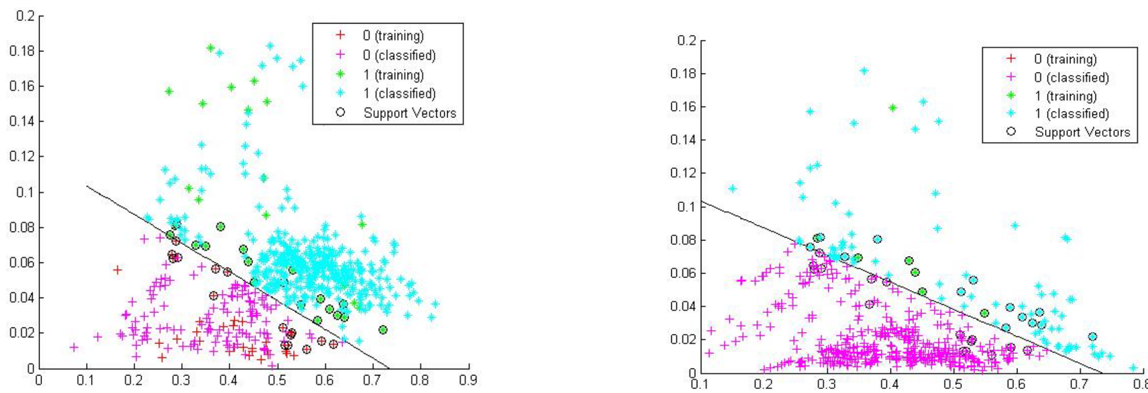

Fig. 15 Scatter diagram for both the images

8. Achievements with respect to the objectives

- All the steps are automatic, no manual steps are required
- Good improvement in CMR is observed using HOG descriptor in case of satellite images with different illumination level.
- Noticeable improvement in CMR is observed if cloudy features are removed using classification. This approach can be made generic approach to improve CMR

9. Conclusion

- For ABM there is little scope of work for satellite IR hence should be preferred if the initial solution is close to the final solution and degree of freedom is minimal, otherwise computation time increases.
- Radon transform properties can be used to find the registration parameters; though the accuracy depends on the resolution of the radon domain

- HOG descriptor can address the illumination variation problem of satellite images. Its use as descriptor in SURF improves the CMR. This leads to the improvement in registration parameters.
- Use of classification before feature matching step, significant improvement in CMR about 20-30% is obtained. This also improves the accuracy of IR. This approach of using classification to remove some of the false matches can be generalized in case of clouds and shadows.

10. Publications

Papers

- Manish I. Patel, V. K. Thakar, "Application of Radon Transform for Fast Image Registration", *2nd International Conference on Advanced Computing and Communication Systems*, Coimbaatore,5-7 Jan. 2015 (available on IEEE explorer)
- Manish I. Patel, V. K. Thakar, "Speed Improvement in Image Registration using Maximum Likelihood based Mutual Information", *2nd International Conference on Advanced Computing and Communication Systems*, Coimbaatore,5-7 Jan. 2015 (available on IEEE explorer)
- Manish I. Patel, V. K. Thakar, Shishir Shah, "Image Registration of Satellite Images with Varying Illumination Level using HOG Descriptor based SURF", - under review to be published in Elsevier

Miscellaneous

- Presented work in special session on PhD Forum During *National Seminar on Computer Vision and Image Processing-2014 (NaSCoVIP-2014)* an IEEE Gujarat section event jointly organized by SCET, Surat and SVNIT, Surat during 19-20, September, 2014
- Attended QIP short term course - on "Advanced Techniques for Satellite Image Analysis" at IIT, Bombay, during 10-14 February, 2014

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