Assessing the Performance of Automatic Co-registration Technique of Satellite Image using Markov Chain-Based Time Series Analysis

Prosenjit Barman & Sk. Mustak*

Department of Geography, Central University of Punjab, Bathinda, India
*Corresponding Author's email: sk.mustak@cup.edu.in

Abstract

Co-registration is an essential task for satellite image-based time series analysis. Co-registration between satellite images is very challenging for urban analysis due to different viewing angles. The relief displacement of an elevated object in images leads to misregistration, affecting the accuracy level in change detection. The main objective of this study is to assess the performance of co-registration on satellite images for time series analysis. The PlanetScope and sentinel multispectral datasets were used for the co-registration. To quantify the average displacement between the different images above 100 checkpoints were established throughout the study area based on the referenced image and filtered the unreliable checkpoints using a feature matching technique. the polynomial affine, conformal, projective transformation were applied. The resampling method has been applied for the pixel-to-pixel coregistration. The accuracy assessment was done using the structural similarity index measure, cross co-relation and Standard Deviation Error. The displacement of two bands has been assessed using Markov chain-based time series analysis. The study shows that the co-registration algorithms with a random distribution of checkpoints provide better accuracy than other distributions. This study helps to develop a cost-effective robust method to improve the accuracy in satellite image-based time series analysis.

Keywords: Co-registration, misregistration, image matching, time series analysis, Markov chain

Introduction

Image registration is a crucial part in remote sensing application for preprocessing of satellite images (Bouchiha & Besbes, 2013; Hassanien & Rahman Shabayek, 2015; Scheffler et al., 2017). Satellite image registration is a crucial component of change detection of the earth, forest, and urban monitoring, as well as national planning-related technologies and policies (Jabari & Zhang, 2016; Martínez-Carricondo et al., 2022; Stumpf et al., 2018). The significance of image registration stems from various elements that impact image registration, including variations in sensor properties, nadir view types, distortions, object movement, and high computational complexity that compromises registration accuracy (Vakalopoulou et al., 2016). Image registration techniques are increasingly common in the medical industry, where they are used to match two distinct images (Hill et al., 2001). There are two categories for satellite image registration techniques: feature-based (FBM) and area-based, or intensity-based approach (ABM) (Sedaghat & Ebadi, 2015). The intensity of each pixel in an image is utilised in the area-based or intensity-based technique to calculate various similarity metrics, such as the cost function, which helps identify the best transformation. However, ABM requires greater computing time for large satellite images. Conversely, feature-based matching makes advantage of an image's prominent local features, such as points, lines, edges, etc. (De Falco et al., 2008; M. I. Patel et al., 2016). FBM image registration consists of four steps: feature extraction, feature matching, transformation, and registration (Fan et al., 2013; Lee & Mahmood, 2015). Several feature extraction techniques are used in satellite image registration, including scale invariant feature test (SIFT), local binary pattern (LBP), Histogram of Oriented Gradients (HOGs), accelerated robust feature (SURF), BRISK etc. (Bay et al., 2006; Chandrappa & Anil, 2021; Hassanien & Rahman Shabayek, 2015; M. I. Patel et al., 2016). Hybrid descriptor features were used to improve the satellite image registration accuracy (Chandrappa & Anil, 2021). Ambati et al., (2019) was presented Landsat and sentinel satellite image coregistration using SURF-FANN feature descriptor method to monitor the earth surface frequently. The combined of feature descriptor method SURF-SIFT gives the lowest RMSE as compare to stand alone method. M. I. Patel et al., (2016) was addressed multi modal, multi sensorial and multi spectral satellite images with varying illumination level for the image coregistration. Histogram of oriented Gradient (HOG) along with speed up robust feature (SURF) was applied for the different illumination level image co-registration. Following feature detection, the feature matching technique was used to register the images. A suitable transformation approach is employed after brute force feature matching, KNN, and other feature matching techniques have been applied to match features and distort the target picture to align with the reference image (Bozorgi & Jafari, 2017; Yang et al., 2017). Piecewise linear (PL), thin plate spline (TPS), and the Affine transformation method are examples of appropriate transformation techniques (Fusion, 2003). The accurate registration of satellite images is effectively improved by the removal of spurious matching points through the use of hybrid feature descriptors along with appropriate transform methods. Hybrid feature descriptor method used to increase the inlier ration and decrease the outlier ratio effectively and improve the SIR accuracy (Chandrappa & Anil, 2021; Pisupati & B, 2020).

Although the use of feature-based techniques for satellite image coregistration has been covered in earlier research, the displacement of reference and coregistered image analysis have lagged behind. This work aim is to present a novel method for automatically detecting the GCPs (or key points) in the distorted and reference images using different feature descriptor method such as SURF, BRISK. The hybrid descriptor helps to provide accurate matching and hence gives us better co-registration results when compared to the existing techniques. The geocoded images were obtained using a variety of transformation algorithms, including conformal, affine, and projective, as well as resampling techniques like bilinear interpolation, nearest neighbor, and cubic convolution. The displacement analysis has been done using Markov chain model.

Materials and Methods

The two-satellite image database of several sensors is used for the coregistration (Fig. 1). The database is available to the public. Figure 1 mentions the example of input satellite image which has been used for coregistration. The registration assessment used the single band of satellite images. The dataset characteristics has been described in a Table 1. The methodological flowchart for the automatic coregistration has been mentioned in figure 2.

Figure 2 explains the process of feature extraction, feature matching, transformation and resampling to register the satellite image.

Image preprocessing: A critical component of image processing is the histogram equalization. it is highly required before applying the feature description for image registration. One common pretreatment method used for satellite image registration is Histogram Equalization (HE). The method of histogram equalisation involves adjusting an image's grayscale value distribution to create a consistent distribution throughout (Chandrappa & Anil, 2021). The mathematical equation of histogram equalization (Eq. 1)

$$s=Tr \qquad \text{Eq. (1)}$$

Where s is the new grayscale, T is the transformation and r is the changed grayscale of pixel.

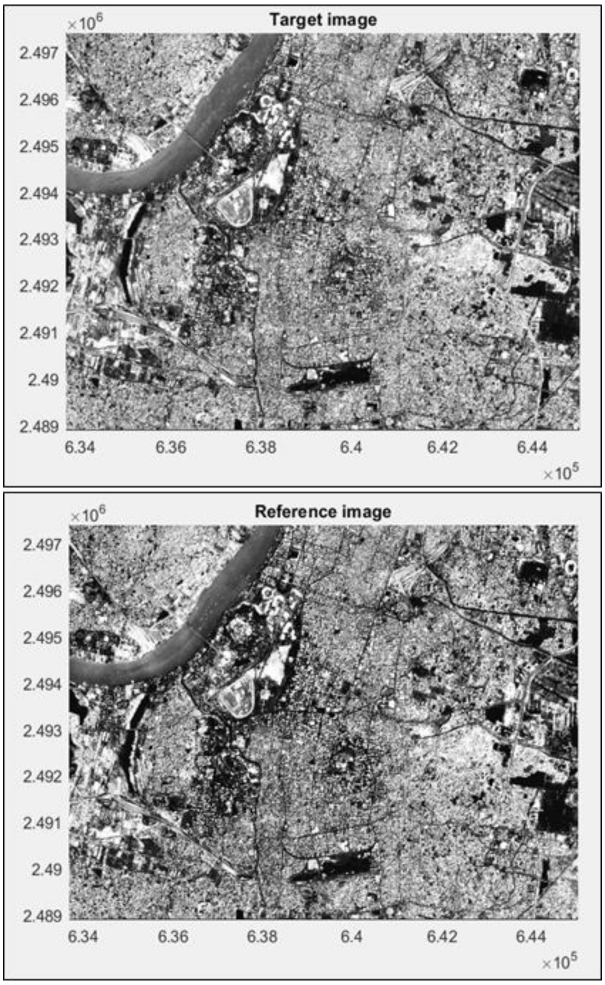

Fig.1 Datasets (Top) Sentinel dataset red band as target image. (Down) Planet data red band as reference.

Table 3 Description of satellite image characteristics.

Type	Planetscope	Sentinel
Band number	Band 6 (Red)	Band 4 (Red)
Resolution	3 meters	10 meters
Acquisition date	Nov, 2023	March, 2023
Geolocation	Orbital altitude	Orthorectified

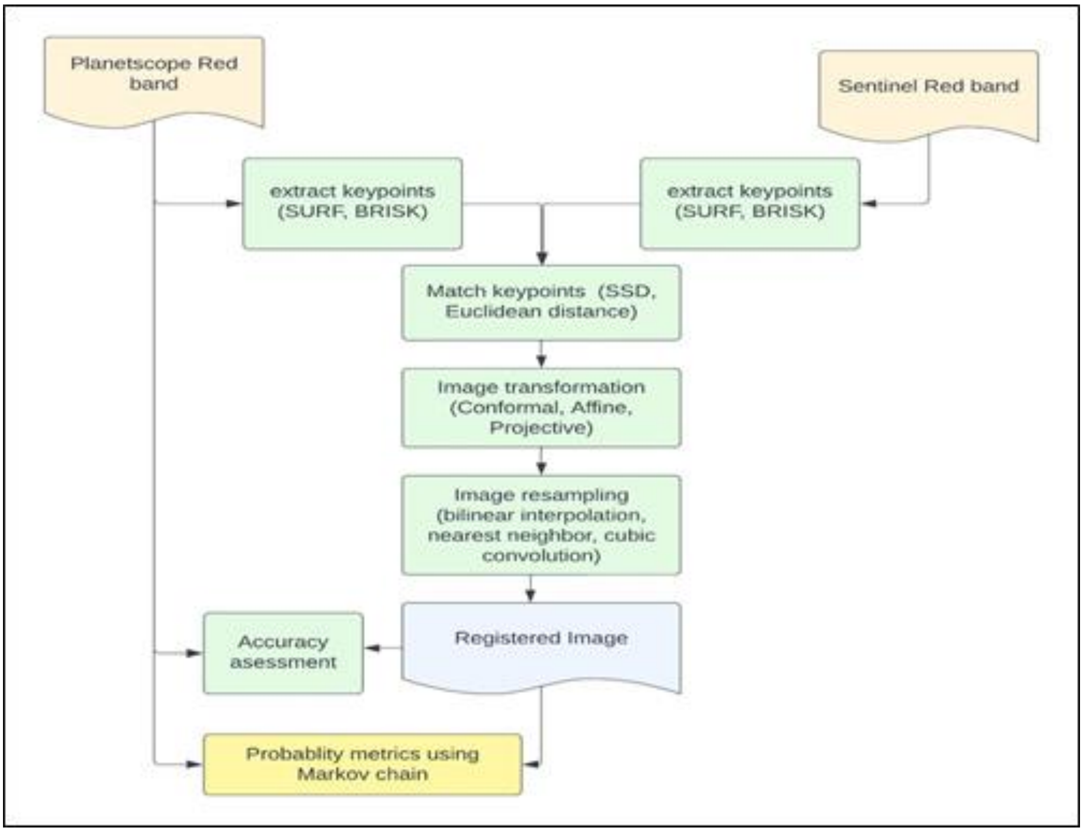

Fig. 2 Methodological flowchart for automatic registration.

Feature detector in satellite image registration: A crucial stage in the automatic image registration process for satellite image registration is feature recognition. Various feature descriptor algorithms, including SIFT, SURF, and FAST, are employed to detect the features (Bay et al., 2006; Hassanien & Rahman Shabayek, 2015; M. I. Patel et al., 2016). SURF, BRISK and hybrid feature descriptors are used in this research study to extract pertinent features from satellite images.

SURF descriptor: The SURF is a local feature descriptor in coregistration approach. SURF is a SIFT-inspired scale and rotation invariant interest point detector and features descriptor. It primarily addresses object identification, image registration, and the detection of rotation and scale at the closest neighbour point of interest (Durgam et al., 2016; M. S. Patel et al., 2016). The fast hessian matrix and scale space theory are used to locate the SURF spots in an image. the SURF descriptor is a durable, repeatable, fast, and distinctive method as Compared to other descriptors (Bay et al., 2006).

BRISK point descriptor: The BRISK is a texture descriptor used in image coregistration as a feature descriptor technique. It quickly extracts the important essential points from an input image while maintaining the quality of matching. In this feature descriptor, a symmetric sampling pattern is applied over the closest sample point of a smooth pixel. BRISK performs as well as state-of-the-art algorithms in terms of adaptability and quality, but at a much reduced computational cost (Leutenegger et al., 2011).

Feature matching: A crucial method for image registration is feature matching. Automatic and reliable feature matching utilising well-distributed points in very high-resolution images is a challenging issue due to large relief displacement induced by towering structures and ground relief (Sedaghat & Ebadi, 2015).

Sum of squared difference: The intensity difference between two images is quantified pixel by pixel using the sum of squared difference feature matching (Hisham et al., 2015). It estimates the summation of squared product of pixels subtraction between two images. The equation for the SSD calculation in digital form is represented in equation 2.

SSDi, j= i=0Mj=0Nfi, j-gi+u, j+v2 Eq. (2)

Where, M size of rows in reference image, N is size of column, u and v are variable. Whether The value of SSD is constant or not depends on the value of variable u and v (Chandrappa & Anil, 2021).

Euclidean distance: Vector-based feature matching can be accomplished using the nearest-neighbour matching in the feature space of the image descriptors in Euclidean norm. It is necessary for the ratio between the distances to the closest and next closest image descriptor to be smaller than a certain threshold. it is most frequently employed to quantify similarity in image retrieval. Following feature extraction, the similarity between the two feature sets from the reference and sensed image is computed using Euclidean distance-based feature matching techniques and SSD feature matching techniques.

Transformation methods

Affine transformation: The affine transformation has a matching approach that properly matches the two satellite images, even though they were acquired from separate positions but the same view angle (Chumchob & Chen, 2008). This feature matching technique is suitable to describe the mapping between the image pairs as the simplest non-rigid transformation. Affine transformations fix an image's global distortions and allow for global alignment of the two pictures for registration of their primary anatomical structures. The equation of affine transformation has been mentioned below

P=Ap+t Eq. (3)

Where, A and t are affine transformation matrix and translation vector respectively. And p is the linear translation (Chandrappa & Anil, 2021; Chumchob & Chen, 2008).

Projective transformation: The relationship between two parallel images is described through projective transformation. It can explain how two unparallel images are transformed with three translations, three rotations, and two scaling effects (Jhan & Rau, 2019). After applying the RANSAC model based on projective transformation, the inliers were used to produce the projective transformation matrix.

Conformal transformation: Conformal transformation is the term used to describe linear transformation. When the input image is deformed by a mix of translation, rotation, and scale but the forms remain unaltered, apply this transformation.

Accuracy assessment: the accuracy assessment of coregistered image was performed using correlation coefficient and Root mean square error techniques. The correlation coefficient was measured using the equation (Vishwakarma Scholar et al., 2018).

c=xyAxy -ĀBxy -B√xxAxy -Ā2xyBxy -B2 Eq. (4)

Where A is mean of pixel value of first image; B is mean of pixel value of second image

The root mean square error (RMSE) measures the average difference between values that a statistical model predicts and the actual values. It is the residuals' standard deviation in mathematics. The RMSE measures the degree to which these residuals are scattered, providing insight into how well the observed data adheres to the expected values. A metric called the Structural Similarity Index (SSIM) is used to determine how similar two images are to one another**.** It measures the reduction in image quality brought on by processing steps like data compression or transmission losses. In actuality, SSIM quantifies the perceptual distinction between two comparable images.

Probability analysis using Markov chain: Transition probability matrix of reference and target image has been calculated. The transition probability matrix has been calculated using markov chain simulation model. First the registered and reference image has been segmented using cluster analysis. The transition probability matrix of segmented classes of reference and target image has been calculated which help to support for time series analysis.

Results

This section provides a full characterization of the experimental results. All experiment was carried out using MATLAB (version 2021B). The image registration procedure uses the point detection algorithm known as BRISK and SURF features. The article describes the matching point utilising BRISK, SURF and hybrid features. The inliers, outliers, of matching point and their distribution as well as registered image has been shown in various figures.

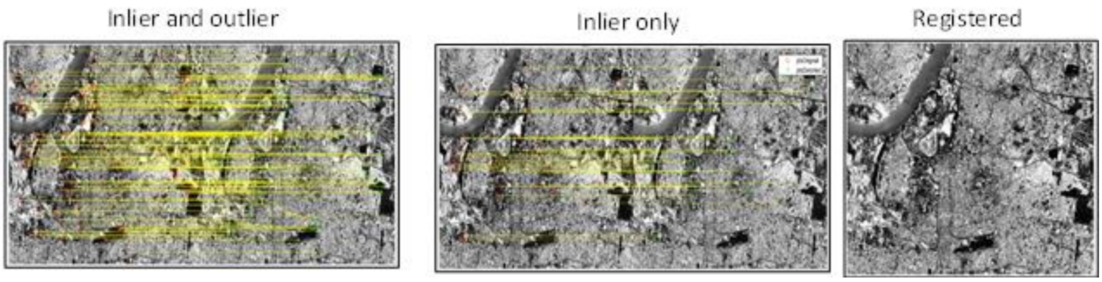

Fig. 3 Brisk feature descriptor (left) inlier and outlier (middle) inlier inly (right) registered image.

Figure 3 shows the performance of BRISK feature for the automate feature detection in image matching. The pair-wise distance between the feature vectors was calculated in order to detect and match the points. the RANSAC feature matching technique has been used to eliminate outliers. The detected key points, with outliers and inlier distribution has been plotted in scatter plot diagram (figure 4). A conformal, affine, or projective transformation method has then been used to register the updated matching points. The transformed image has been resampled using different resampling technique for the pixel-to-pixel registration.

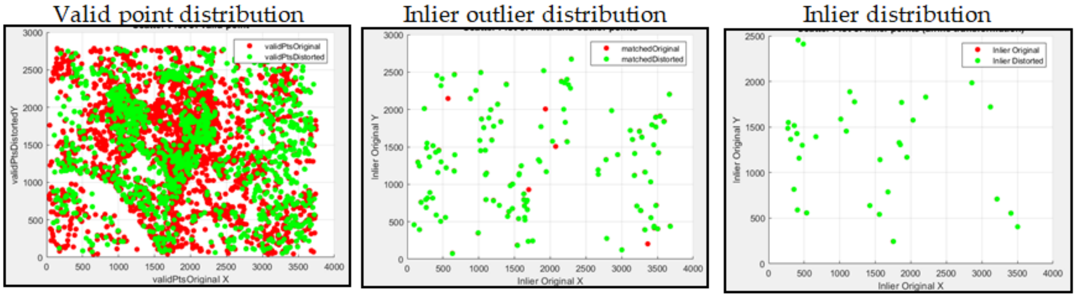

Fig. 4 Distribution of feature points of extracted key points in reference and target image.

The SURF feature detector technique has been applied for the satellite image registration. SURF detector matching points with outlier, matched points with inlier and registered image have been displayed in figure 5. The figure 6 shows the distribution of matched points with outlier as well as inlier. The SSD feature matching technique was used to match the relevant points in the SURF feature. The distributed feature points are large but the matched points are very low. After the transformation the matched key points has also been reduced. This inlier points warps on the target image to assist in producing a registered image. Pixel-to-pixel auto co-registration has been enabled by resampling the registered image.

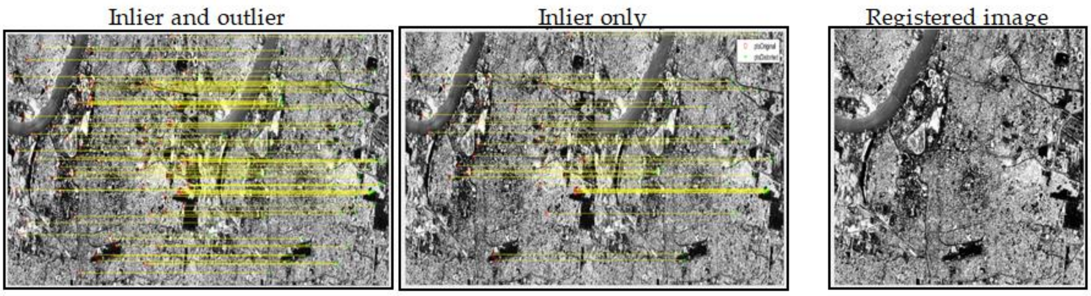

Fig. 5 Matching point using SURF with inliers and outliers, only with inliers and registered image.

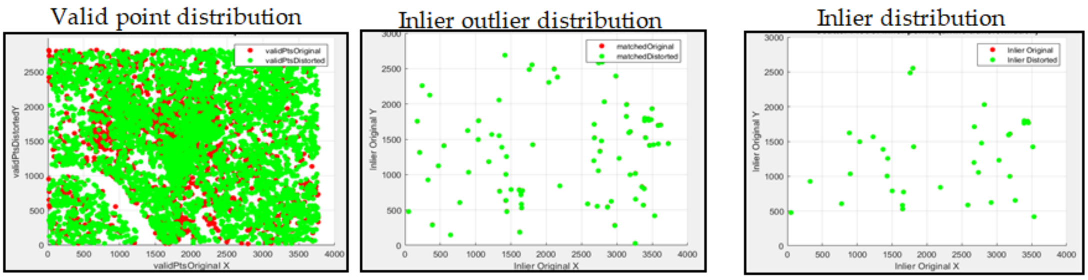

Fig. 6 Distribution of feature points with SURF extracted features.

The hybrid feature descriptor (BRISK and SURF) has been applied for image registration to increase the matched points of reference and registered image (figure 7). The associated features of two images are matched by the combination of BRISK and SURF features. The distributed points of hybrid feature matched points with outlier and inlier has been plotted in figure 8.

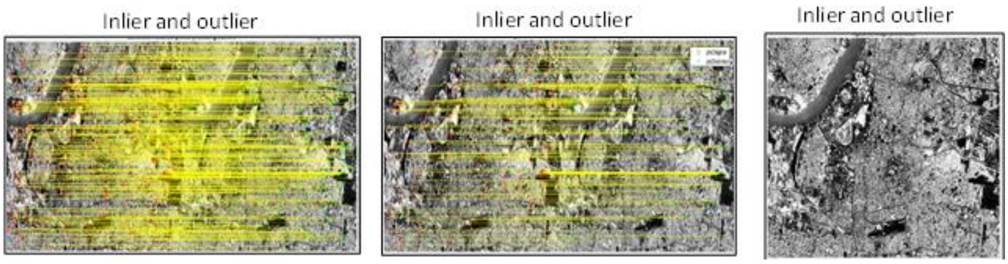

Fig. 7 Surf and Brisk hybrid feature image registration.

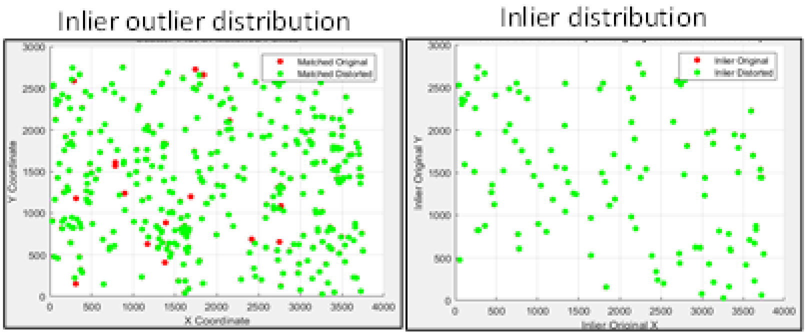

Fig. 8 Distribution of feature points.

The quality of satellite image co-registration in this experiment is dependent on a number of geometrical transformations and resampling methods. The BRISK, SURF produces a comparable result when comparing the geometrical transformations. However, the combination of SURF and BRISK produces a good matching outcome for image registration.

Discussion

The feature descriptor performance of BRISK and SURF as individual feature descriptors and of the combined feature descriptors BRISK + SURF has been analysed in Table 2. Outliers indicate an erroneous feature prediction, whereas inliers indicate a successful feature prediction. The table describes that projective transformation with cubic resampling technique gives the highest accuracy. Cross corelation of this technique in SURF detector algorithm is high. Conformal transformation with cubic sample gives the high accuracy. The textural similarity and cross corelation is high. Hybrid feature descriptor produces the highest accuracy as compare to individual algorithm. Affine transformation with cubic resampling produces the high accuracy. The SSIM and cross corelation level is high. Local descriptors were used for multispectral images in image registration. In order to remove the scale difference, translation, and rotation discrepancies between the reference and sensed images (Ye and Shan, 2014). The inlier ratio of feature descriptor algorithm has been plotted in figure 9. SURF descriptor produces the highest inlier ratio as compare to BRISK and hybrid features. Conformal transformation produces highest inlier ratio as compare to affine and projective transformation. Hybrid feature descriptor also produces comparable result in inler ratio. A suitable transform method is applied to hybrid feature descriptors in order to eliminate incorrect matching locations. More incorrect matching points are eliminated, which effectively increases SIR accuracy (Chandrappa & Anil, (2021). The displacement of reference and registered image analysis has been measured. The segmented classes transformation probability matrix has been shown in Table 3.

Table 4. Accuracy assessment of feature descriptor

Models	RMSD			SSIM			Cros correlation		
	SURF	BRISK	SURF+BRISK	SURF	BRISK	SURF + Brisk	SURF	BRISK	SURF + BRISK
Conformal + bilinear	0.52	0.95	0.82	0.45	0.440	0.41	0.84	0.83	0.84
Conformal + nearest neighbor	1.82	0.95	0.92	0.44	0.435	0.40	0.84	0.83	0.84
Conformal + cubic	0.61	0.69	0.42	0.45	0.439	0.41	0.84	0.83	0.84
Affine + bilinear	0.83	0.94	0.59	0.44	0.439	0.41	0.83	0.84	0.84
Affine + nearest neighbor	0.84	0.95	0.80	0.44	0.435	0.40	0.83	0.83	0.84
Affine + cubic	0.73	0.74	0.39	0.43	0.438	0.46	0.83	0.84	0.84
Projective + bilinear	0.84	1.20	0.83	0.45	0.381	0.43	0.84	0.78	0.83
Projective + nearest neighbor	0.91	1.22	0.94	0.45	0.368	0.43	0.84	0.77	0.82
Projective + cubic	0.42	0.89	0.83	0.44	0.370	0.43	0.84	0.78	0.82

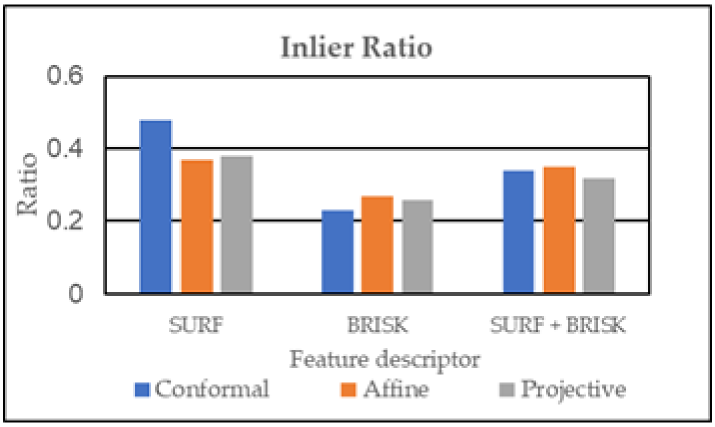

Fig. 9 Inlier ratio of feature descriptor.

Table 5 Probability matrix of segmented classes.

	Class 1		Class 2		Class 3		Class 4		Class 5	
	Distorted	Registered	Distorted	Registered	Distorted	Registered	Distorted	Registered	Distorted	Registered
Class 1	0.4038	0.4012	0.2121	0.2114	0.3039	0.3006	0.0373	0.0418	0.0429	0.0450
Class 2	0.1002	0.1017	0.0217	0.0259	0.3230	0.3211	0.0029	0.0047	0.5523	0.5466
Class 3	0.0602	0.0657	0.2604	0.2593	0.0083	0.0121	0.6701	0.6617	0.0009	0.0012
Class 4	0.2540	0.2488	0.4893	0.4902	0.0465	0.0523	0.2077	0.2051	0.0025	0.0036
Class 5	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.000	0.000

Conclusion

IR is the technique of aligning the two images of different sensors with time consuming. This study suggests a hybrid feature descriptor (SURF + BRISK) to increase SIR. In addition, a transformation technique is used to prevent false feature matching points. Transformation methods such as affine, conformal, projective transformation avoids the false feature matching points and signify the registered image. Sampling techniques also helps to improve co-reregister accuracy. In this study only feature based descriptor was used and compare but there has other descriptor like intensity-based descriptor, AROSICS can be used and compare their accuracy for further study. In the present research work, the proposed approaches used the different sensor and single band, multiple sensor multiple images will be used in future work for satellite image matcing and registration.

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