International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
Vol.4, No.12, December 2015 DOI:10.15693/ijaist/2015.v4i12.58-66

Automatic Satellite Image Registration: A Survey

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***Abstract*— This paper aims to present a review of various techniques used for automatic satellite image registration. Image registration is the first step towards using the satellite images for any purpose. It is the fundamental task used to match two or more partially overlapping multi view, multi modal or multi temporal images and stitches these images into one image comprising the whole scene. Automatic satellite image registration is a challenging task of overlaying two images for geometric conformity aligning common features by establishing a transformation model using distinguishable feature points collected simultaneously in reference image and the sensed images in a completely unassisted manner. This requires intensive computational effort not only because of its computational complexity, but also due to the continuous increase in image resolution and spectral bands. Thus, high-performance computing techniques for image registration are critically needed. The reviewed approach is classified according to four basic steps of feature based image registration: *feature detection, feature matching, transform model estimation and image transformation and resampling*. The advantages and disadvantages of the techniques are mentioned in this paper. The major goal of the paper is to provide a comprehensive reference source for the researchers involved in automatic satellite image registration.**

Index terms — Automatic satellite image registration, Feature detection, Feature matching, Image transformation and resampling, Transform model estimation

I. INTRODUCTION

Image registration is the process of geometrically aligning two or more images of the same scene taken by different sensors, at different times, and/or from different viewpoints. It geometrically aligns two images—the reference image and the sensed image [1]. The image with respect to which the alignment is carried out is called the reference image. The image which is aligned is called the sensed image. The transformed sensed image which aligns with the reference is called registered image [2].

The main idea behind the any image registration process is that the sensed image undergoes the registration process and its pixel coordinates are converted into the reference image pixel coordinates. In this way we get the transformed sensed image. Then this transformed sensed image is super imposed on the reference image in visually plausible way. Once we have super imposed both the images then we have a larger 2D view of the scene or highly informative single output image [3].

Image registration is the foundation of applications, such as image fusion, medical image processing, remote sensing and three dimensional (3D) image reconstructions [4].

Image registration application can be divided into four main groups depending upon how the images are acquired which are to be registered [1]:

- Multiview analysis
- Multitemporal analysis
- Multimodal analysis
- Scene to model registration

Multiview analysis (different viewpoints): Images are acquired from different viewpoints of the same scene. The goal is to gain larger a 2D view or a 3D representation of the scanned scene.

Examples of applications: Remote sensing: mosaicing of images of the surveyed area. Computer vision: shape recovery.

Multitemporal analysis (Different times): Images are acquired at different times, often on regular basis, and possibly under different conditions of the same scene. The goal is to find and evaluate changes in the scene which appeared between the consecutive image acquisitions.

Examples of applications: Remote sensing: monitoring of global land usage, landscape planning. Computer vision—automatic change detection for security monitoring, motion tracking. Medical imaging: monitoring of the healing therapy, monitoring of the tumor evolution.

Multimodal analysis (Different sensors): Images are acquired by different sensors of the same scene. The goal is to integrate the information obtained from different source streams to gain more complex and detailed scene representation.

Examples of applications: Remote sensing: fusion of information from sensors with different characteristics like panchromatic images, offering better spatial resolution, color/multispectral images with better spectral resolution, or radar images independent of cloud cover and solar illumination. Medical imaging: combination of sensors recording the anatomical body structure like magnetic resonance image (MRI), ultrasound or CT with sensors monitoring functional and metabolic body activities like positron emission tomography (PET), single photon emission computed tomography (SPECT) or magnetic resonance spectroscopy (MRS). Results can be applied, for instance, in radiotherapy and nuclear medicine.

Scene to model registration: A model of the scene and images of a scene are registered. The model can be a computer representation of the scene, for instance digital elevation models (DEM) in GIS or maps, another scene with similar content, etc. The goal is to localize the acquired image in the scene/model and/or to compare them.

Examples of applications: Remote sensing: registration of aerial or satellite data into maps or other GIS layers. Computer vision: target template matching with real-time images, automatic quality inspection. Medical imaging: comparison of the patient's image with digital anatomical atlases, specimen classification.

For each of the group of the image registration application mentioned above, there are two types of image registration named as area based image registration and feature based image registration. The area based methods are used when distinctive and important information is provided by pixel intensity [1]. They use some statistical information to measure the degree of similarity of the whole image [5]. The feature based methods are used when important information is given by the image features like point, edge, corners, and contours [6].

In remote sensing applications, while registering the satellite images there are several unique challenges like cloudpixels, noise in the images, systematic errors, multispectral images, terrain induced distortions etc [7]. Image registration process can itself generate noise in the registered image, which can be perceived as blurring effect, change in brightness and contrast levels etc. Hence in this process, accuracy can be justified if registered image is devoid of noise [8]. A high-resolution satellite image can be several hundred megapixels in size and occupy several spectral bands. Although high-resolution images provide detailed information, it is inefficient to process the entire image due to limited resources such as memory and storage. High-resolution satellite images also contain local distortions because of different sensors having different paths, angles, and terrain relief, i.e., the number of feature points and distribution quality affect the accuracy [9]. For multimodal images, finding a common region is difficult particularly when the pixel intensity distribution is different and different sensors share different pixel information. So feature matching is also difficult.

Compared to area based methods, feature based methods are more widely applied in remote sensing application due to their advantages. The area based methods find correspondences in the image space whereas the feature based methods find correspondences in the feature space which represents information at higher and abstract level. If there is complex distortion between the images to be aligned, then the computational complexity or the search space of the area based methods increases nonlinearly with the transformation complexity. The feature-based methods can overcome this drawback as their search space is proportional to the number of features detected from the images. Sometimes the selected features are invariant to the changes of the image's geometric and radiometric conditions, presence of noise, and the changes in the target scene. Therefore, this type of method is suitable for the situations where multisensor analysis is demanded or illumination changes are expected [10]. Feature-based methods are capable of registering the images with distinctive features, such as map and photograph, as well as those with complex distortions [11]. One of the main advantages of feature based methods is that they are fast and robust to noises, significant radiometric differences, and complex geometric distortions [12].

In remote sensing applications, the conventional image registration is generally carried out. Conventional image registration techniques involve manual selection of control points (CPs) which are used to estimate the geometric transformation model that establishes a mapping between reference and sensed image. Manual registration is not feasible in the cases where large amount of data is to be processed. Also the conventional method needs an expert with a special skill to select the individual CPs precisely for estimating the transformation model which is a laborious activity. Thus, automated techniques that require little or no operator supervision is needed. An Automatic Image Registration (AIR) technique can solve the drawbacks of conventional methods and it is a highly desirable requirement of the remote sensing world to deal with large volumes of satellite data available for quick and accurate registration [13], [14], [15]. The main concept of automatic image registration for satellite images is to obtain acute set of CPs and then apply the transformation model which is most suitable to the pair of images to be registered [16].

In section II, the steps of feature based satellite image registration are described. Section III and section IV comprises of approaches for feature detection and feature matching respectively. Section V and section VI describes the various transform model estimations and various techniques for image transformation and resampling respectively. Finally section VII covers the evaluation of the image registration accuracy.

II. IMAGE REGISTRATION METHODOLOGY

Feature based image registration, as it was mentioned above, is widely used in remote sensing application. There are four fundamental steps for feature based satellite image registration as given below [1].

A. Feature detection

Salient and distinctive objects like closed-boundary regions, edges, contours, line intersections, corners, etc. are automatically detected. For further processing, these features can be represented by their point representatives like centers of gravity, line endings, distinctive points which are called control points (CPs) in the literature.

B. Feature matching

In this step, the correspondence between the features detected in the sensed image and those detected in the reference image is established. Various feature descriptors and similarity measures are used for that purpose.

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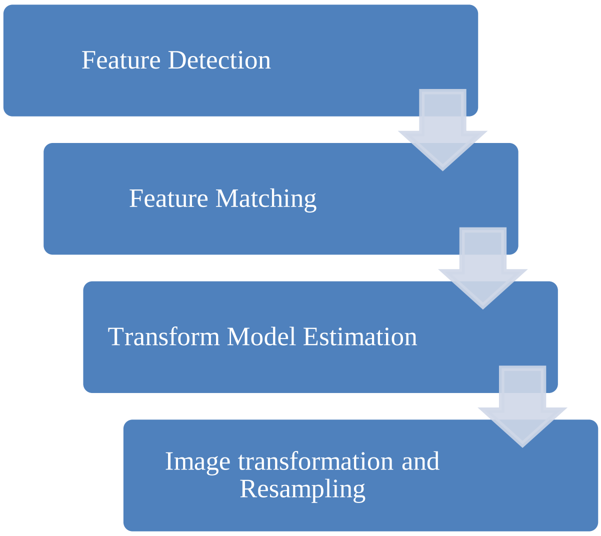

Figure 1. Fundamental steps for feature based image registration[1].

C. *Transform model estimation*

The type and parameters of the so-called mapping functions, aligning the sensed image with the reference image, are estimated. The parameters of the mapping functions are computed by means of the established feature correspondence in the 2nd step.

D. *Image transformation and resampling*

The sensed image is transformed by means of the mapping functions. Image values in non-integer coordinates are computed by the appropriate interpolation technique.

III. Feature Detection

Formerly, the features were selected manually by an expert. But today lots of automatic feature detection methods and algorithms are available which does not require any human interaction. The reviewed feature detectors are shown in fig. 2.

A. *Feature detection Adaptive Phase Congruency Feature Detector (APCFD) :*

This is a candidate-selection method which ensures that only significant CPs are detected. First minimum moment map for the image is determined. Then threshold is set to a low threshold t_o, and preliminary candidates are selected as points that are a local maximum within a fixed radius r and have a corner strength greater than t_o. After that only the strongest n candidates are selected as the final set of CP candidates, where n is the number of candidate points desired. The effective threshold is adaptive to allow for the desired number of candidate points to be retained. After the selection of the candidate points, the position of a CP candidate is readjusted for subpixel accuracy by fitting a 2-D quadratic to the corner strength in its local neighborhood and then finding the maximum of the quadratic. This detector is illumination and contrast invariant [17].

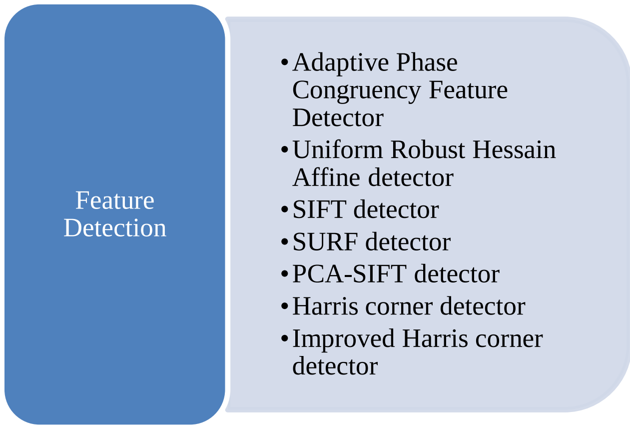

Figure 2. Reviewed methods for feature detection.

B. *Uniform Robust Hessain Affine detector*

It is designed to increase the capability of Hessain affine detector in remote sensing images. It is based on the selection strategy of the features in the full distribution of the location and the scale where the feature qualities are quarantined based on the stability and distinctiveness constraints. The *contrast*, *entropy*, and *scale* of each candidate Hessian affine feature are considered for feature quality evaluation, and multilevel gridding is used for location distribution. It has high capability in robust and uniform scale and spatial distribution feature extraction [18].

C. *SIFT detector*

Scale Invariant Feature Transform (SIFT) detector detects the local extrema in scale space as candidate feature by approximating the Laplacian with difference of Gaussian filter [19] [20]. It allows distinctive invariant feature extraction from images and it can be applied to perform reliable matching between sensed and reference image presenting a substantial range of affine distortion, addition of noise, changes in illumination and change in 3-D viewpoint [16]. SIFT detector improves the detection stability even if the input is noisy. The detected features are highly distinctive. It has proven to be good for multi-angle imagery [21].

It is invariant to scale, illumination changes, rotation and is preferable to certain extent in 3D camera viewpoint [21] [19]. It can be ineffective in finding CPs for high view angles in areas with low elevation differences [21]. It suffers from high complexity while extracting feature points and it also lacks in feature points and distribution quality [9].

D. *SURF detector*

Speeded Up Robust Feature (SURF) is a scale invariant feature detector that uses integral images and Hessain matrix for very fast computation of detectors. Using a set of box filters, Hessain matrix is roughly approximated and no smoothing is applied when going from one scale to another. SURF approximates second order derivatives. SURF is five times faster than Difference of Gaussian [22]. It has low accuracy and processing time is slightly improved as compared to SIFT [9]. It detects less number of features as compared to SIFT [23]. It is fast detector but it is not stable to rotation and illumination changes [24].

E. PCA-SIFT detector

Principle Component Analysis (PCA) is a technique for dimensionality reduction. It enables us to linearly-project high dimensional samples into low dimension feature space. PCA-SIFT use PCA to normalize gradient patches instead of histogram. The feature vector is significantly smaller than SIFT feature vector [24]. It reduces the feature space by selecting only important features and thus reduces the time complexity. But the accuracy is low and processing time is slightly improved than SIFT [9]. The performance is good for time, rotation, illumination and affine but has poor performance for blur and scale [24].

F. Harris corner detector

The Harris corner detector is based on the local auto correlation function of the signal. This detector determines whether a point shows significant change in all the directions to designate it as a corner point. It has invariant to rotation, translation and illumination change. It is most informative and most repetitive detector [22]. The drawback of this detector is that it is not invariant to large scale change [25]. Modifications are performed on the standard Harris corner detector which gives better performance in several conditions. Harris-Laplace and Harris-Affine are scale and affine invariant versions of standard Harris corner detector [22].

G. Improved Harris corner detector

This detector uses only first-order derivatives and is one of the most stable and robust corner detectors [15]. It gives better result than Harris corner detector in case of rotation, scaling, illumination changes and viewpoint change. The interest points are largely independent of the imaging conditions and are geometrically stable for this detector [25]. In Harris corner detector, the corner response function involves the use of constant parameter k [26]. For better result, k=0.04 should be used [27]. Now in improved Harris corner detector, the corner response function is modified and is made independent of constant parameter k [28].

IV. FEATURE MATCHING

Once the features are detected from the reference and the sensed image, the next step is to find the correspondence between the detected features. In the feature matching step, our goal is to find out which feature of the reference image is corresponding to which features in the sensed image [1]. The reviewed feature matching methods are shown in fig. 3.

A. Normalized cross correlation (NCC) method

The classical representative of the feature matching methods is the NCC. This measure of similarity is computed for window pairs from the reference and sensed images and its maximum is searched [13]. The window pairs for which the maximum is achieved are set as the corresponding ones. Although the CC based registration can exactly align mutually translated images only, it can also be successfully applied when slight scaling and rotation are present. There are generalized versions of CC for geometrically more deformed images. They compute the CC for each assumed geometric transformation of the sensed image window and are able to handle even more complicated geometric deformations than the translation-usually the similarity transform. The computational load, however, grows very fast with the increase of the transformation complexity. Recently big interest in the area of multimodal registration has been paid to the correlation ratio based methods. In opposite to classical CC, this similarity measure can handle intensity differences between images due to the usage of different sensors-multimodal images. It supposes that intensity dependence can be represented by some function.

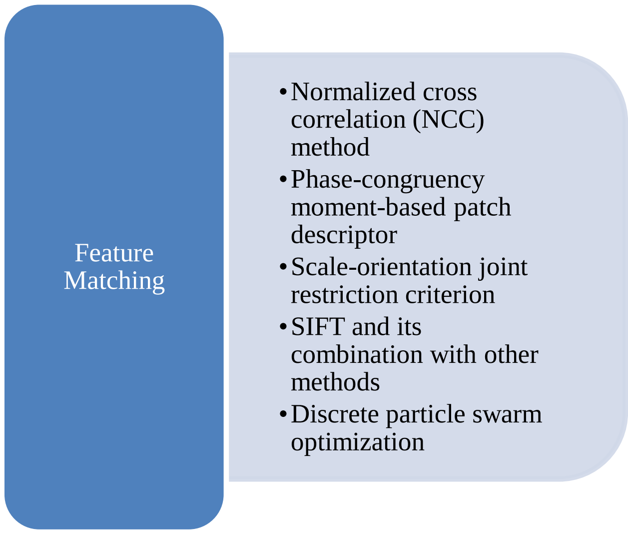

Figure 3. Reviewed methods for feature matching.

Two main drawbacks of the correlation-like methods are the flatness of the similarity measure maxima (due to the self-similarity of the images) and high computational complexity. The maximum can be sharpened by pre-processing or by using the edge or vector correlation. Despite the limitations mentioned above, the correlation like registration methods are still often in use, particularly thanks to their easy hardware implementation, which makes them useful for real-time applications.

B. Phase-congruency moment-based patch descriptor

The maximum moment of phase congruency gives a good representation of structural feature significance within an image. High value of phase congruency indicates high structural feature significance. This descriptor is invariant to illumination and contrast variations. It is also invariant to intensity mappings. This descriptor is suitable for both intrasensor and intersensor images as different modalities can have very different intensity mappings [17].

C. Scale-orientation joint restriction criterion

This criterion uses Joint distance (JD) instead of Euclidean distance as distance measure. It was used to solve the problems of incorrect matches of keypoint due to significant difference in image intensity between remotely sensed images using SIFT descriptor. Initially, for each keypoint, Euclidean distance ratio (ED-R) filter is used and threshold is set to obtain keypoint pair cross correlation (CC). After that scale ratio histogram and relative main orientation is built. Peaks in the two histograms are found using an adaptive threshold. This is done to obtain all candidates clustering center of scale factor and the rotation angle. Then matching step uses these candidates as the JD-R filter's input and find the ground truth of the clustering center by minimizing JD. Finally, thresholding is used to eliminate false matches from CC. This method gives higher correct match rate and aligning accuracy than SIFT for multi-sensor, multi-spectral and multi-temporal remote images [20].

D. SIFT and its combination with other methods

Scale invariant feature transform (SIFT) descriptor is a 3-D histogram of gradient location and orientation. The location is quantized into a 4×4 location grid. The gradient angle is quantized into eight orientations resulting in descriptor of dimension 128. SIFT descriptor performs reliable matching between images presenting a substantial range of affine distortion, addition of noise, change in 3-D view and change in illumination [16]. Despite of several attractive advantages of SIFT descriptor, it does not produce meaningful results when directly applied to remotely sensed images [16], [12]. The number of detected feature matches may be small and their distribution may be uneven due to complex content nature of remote sensing images. Also, many outliers exist in feature matches because of significant differences on image intensity between the overlay regions of remote sensing images [12].

A novel to course-to-fine strategy for automatic image registration based on SIFT and mutual information (MI) is proposed by Maoguo Gong etal. [12]. This technique involves preregistration process which is implemented by the SIFT approach equipped with a reliable outlier removal procedure. By means of its distinctiveness and invariance, SIFT results in robust matching. The modified outlier removal method can generally eliminate most incorrect SIFT matches and can retain most correct ones by means of its robustness. The results obtained by the preregistration process provide a near-optimal initial solution for the optimizer in the fine-tuning process. Next, the fine tuning process is implemented by maximization of MI using the modified Marquardt–Levenberg search strategy in a multiresolution framework which increases the robustness of the algorithm and can significantly improve its computational efficiency.

J. Senthilnath etal. [29] compared the performance of SIFT with Genetic Algorithm (SIFT-GA) and SIFT with Approximate Nearest Neighbor (SIFT-ANN) for multi-sensor remote sensing images for flood assessment and concluded that SIFT-GA is able to match large number of keypoints while SIFT-ANN is able to give few correct matches with large number of mismatch for less flooded areas. Both SIFT-GA and SIFT-ANN failed to match keypoints in completely flooded regions due to large scene change.

Amin Sedaghat etal. [18] proposed adaptive binning scale invariant feature transform (AB-SIFT) for fully automatic remote sensing image matching. The main idea of AB-SIFT is an adaptive binning strategy to compute the local feature descriptor. It is computed on a normalized region defined by the uniform robust Hessian affine algorithm. AB-SIFT use an adaptive histogram quantization strategy for both location and gradient orientations, which is robust and resistant to a local viewpoint distortion and extremely increases the discriminability and robustness of the final AB-SIFT descriptor. In addition to the SIFT descriptor, the proposed adaptive quantization strategy can be easily extended for other distribution-based descriptors. AB-SIFT matching method is more robust and accurate than SIFT, DAISY, the gradient location and orientation histogram, the local intensity order pattern, and the binary robust invariant scale keypoint.

E. Discrete particle swarm optimization

Discrete particle swarm optimization (DPSO) is used for matching the features in the reference and the sensed image. DPSO finds three corresponding points in both the images using multi-objective optimization of distance and angle condition through objective switching technique. Using this technique, the global best matched points are obtained. DPSO is more efficient than RANSAC for multi-sensor image registration. The initial population is random and the parameters are set empirically for better match are the few restrictions of DPSO [2]. The optimization through multi-objective fitness function incorporated DPSO is robust as it is able to register image independent of which scheme is applied for corner detection if there is appropriate corner detection [30].

V. TRANSFORM MODEL ESTIMATION

The mapping function is constructed after the feature correspondence has been established. It should transform the sensed image to overlay it over the reference image. The selection of mapping function should correspond to the assumed geometric deformation of the sensed image, to the method of image acquisition and to the required registration accuracy. The mapping function models can be divided into two broad categories according to the image data they use as their support. Global mapping models use all CPs for estimating one set of mapping function parameters valid for entire image. The local mapping models treat the image as a composition of patches and the function parameters depends on the location of their support in the image [1]. The reviewed methods are as shown in fig. 4 and described below.

A. Thin plate splines transformation

Thin plate splines (TPS) are the most often used representatives of radial basis function. It can be viewed as a very thin plate, which is fixed at the position determined by the control points in the reference image in the heights given by the x or y coordinates of the corresponding control points in the sensed image. It minimizes the quadratic variation functional of the potential energy that reflects the amount of function variations. The amount of function variations should

International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
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be small for good mapping function. The registration using TPS gives good results but the computations can be very time consuming [1]. The TPS model can deal with local distortion problem and is key component in reaching subpixel image registration accuracy [21]. The TPS function is a flexible transformation that allows scaling, translation, rotation and skewing. It also allows lines to bend according to TPS model. Therefore large number of deformations can be characterized by TPS model [15].

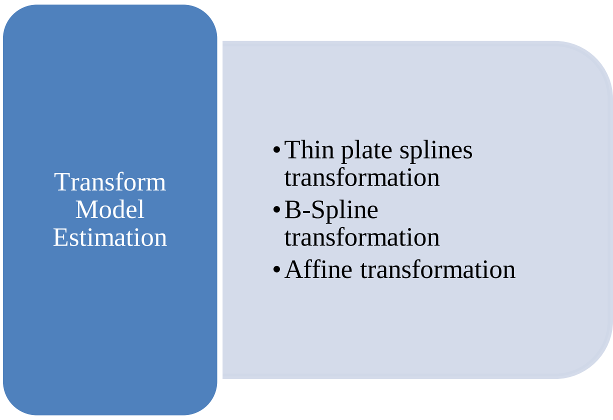

Figure 4. Reviewed methods for transform model estimation.

B. B-Spline transformation

B-Spline model requires a rough pre-alignment to bring the images together such that only local deformations are present. These local deformations can then be modeled using B-Spline. It is robust to noise and is not as dependent on texture. It is locally controlled which makes it computationally efficient even for large number of feature points [9].

C. Affine transformation

Affine transformation is any transformation that preserves collinearity and ratio of distance. It is composed of linear transformations i.e., rotation, scaling or shear, and a translation or shift. Geometric contraction, dilation, expansion, rotation, shear, reflection, similarity and translation are all affine transformation. In the ideal situation, the transformation can be computed from three pairs of noncollinear correspondences (two corresponding points from the reference image and the sensed image, respectively). Therefore, in order to define an affine transformation, it is needed to pick three noncollinear correspondences from the reference image and the sensed image separately [10]. Affine transformation is mostly used for satellite images. Chahira Serief etal. [31], Zhili Song etal. [10], Ye Zhang etal. [32] and Youcef Bentoutou etal. [15] used affine transformation for satellite image registration.

VI. IMAGE TRANSFORMATION AND RESAMPLING

The mapping functions constructed during the transform model estimation are used to transform the sensed image and thus to register the images. The transformation can be realized in a forward or backward manner. Each pixel from the sensed image can be directly transformed using the estimated mapping functions. This approach is called forward method which is complicated to implement as it can produce holes and/or overlaps in the output image. Hence, the backward approach is usually chosen. In backward approach, the registered image data from the sensed image are determined using the coordinates of the target pixel and the inverse of the estimated mapping function. The image interpolation takes place in the sensed image on the regular grid. In this way neither holes nor overlaps can occur in the output image.

The interpolation itself is usually realized via convolution of the image with an interpolation kernel. An optimal interpolant—2D sinc function—is hard to implement in practice because of its infinite extent. Thus, many simpler interpolants of bounded support have been investigated in the literature. In order to reduce the computational cost, preferably separable interpolants have been considered. The separability enables to replace an $m \times m$ 2D convolution by $(m+1)$ 1D convolutions which is much faster. The reviewed methods are as shown in fig. 5 and described below.

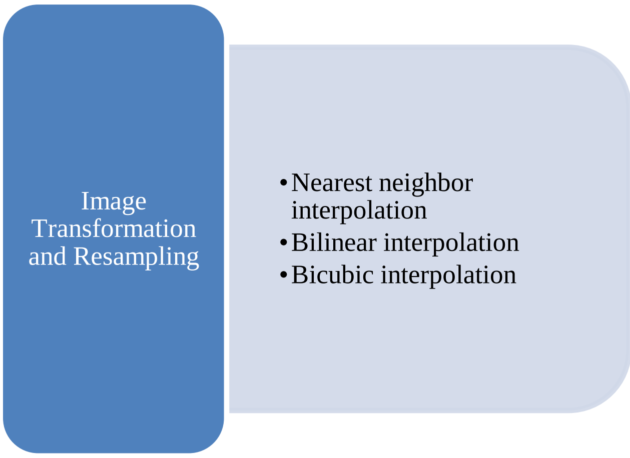

Figure 5. Reviewed methods for image transformation and resampling.

Nearest neighbor interpolation should be avoided in most cases because of artifacts in the resampled image except when the image to be transformed contains low number of intensities and we do not want to introduce synthetic graylevels by higher order interpolation. Even though the bilinear interpolation is outperformed by higher order methods in terms of visual appearance and accuracy of the transformed image, it gives probably the best trade-off between accuracy and computational complexity [1]. The bicubic interpolation requires larger computing time than bilinear interpolation and nearest neighbor interpolation but it gives the highest accuracy and a smoother surface [9].

VII. EVALUATION OF IMAGE REGISTRATION ACCURACY AND PERFORMANCE

A. Localization error

Displacement of the CP coordinates due to their inaccurate detection is called localization error. Localization error can be reduced by selecting an 'optimal' feature detection algorithm for the given data but usually there is a tradeoff between the number of detected CP candidates and the mean localization error. Sometimes we prefer to have more CP with higher localization error rather than only few of them, yet detected more precisely [1].

B. Matching error

Matching error is measured by the number of false matches when establishing the correspondence between CP candidates. It is a serious mistake which usually leads to failure of the registration process and should be avoided. Fortunately, in most cases it can be ensured by robust matching algorithms. False match can be identified by consistency check, where two different matching methods are applied to the same set of the CP candidates. Only those pairs found by the both methods are considered as valid CP pairs, the other candidate points are excluded from the further processing [1].

C. Alignment error

Alignment error is denoted by the difference between the mapping model used for the registration and the actual between-image geometric distortion. Alignment error is always present in practice because of two different reasons. The type of the chosen mapping model may not correspond to the actual distortion and/or the parameters of the model were not calculated precisely. The former case is caused by lack of a priori information about the geometric distortion while the latter originates from the insufficient number of CP's and/or their localization errors [1].

D. Efficiency

Given the large size of remotely sensed images, it is important to minimize the computational effort required to perform each of these steps while maintaining alignment accuracy [17].

E. Robustness

Differences in remotely sensed images of the same scene often exist due to factors such as environmental noise, differences in illumination and contrast, and differences in viewpoint. Therefore, it is important to minimize the effect of such image variances on image registration accuracy [17].

F. Accuracy

Visualization and analysis of remotely sensed data require that a reasonable level of accuracy be achieved during the registration process. Therefore, it is important that the registration process produces an image that is visually and numerically correct [17].

VIII. CONCLUSION

This paper provides the overview of the various techniques for automatic satellite image registration. Manual method is not feasible for large amount of data and needs expert to detect features manually which is laborious activity. Automatic image registration overcomes the drawbacks of manual method and is highly desirable for satellite image registration. From the reviewed methods, it can be concluded that, for feature detection, improved Harris corner detector is best detector. Discrete particle swarm optimization is best method feature matching. Affine transformation gives the best result for all types of images. Bilinear interpolation is generally used which gives the best trade-off between accuracy and computational complexity.

REFERENCES

[1] B.Zitova, J. Flusser, "Image Registration Methods: a survey", Elsevier Image and Vision Computing, pp. 977-1000, 2003.

[2] J. Senthilnath, S. N. Omkar, V. Mani, and T. Karthikeyan, "Multiobjective Discrete Particle Swarm Optimization for Multisensor Image Alignment", IEEE Geoscience and Remote Sensing Letters, Vol. 10, No. 5, pp. 1095-1099, 2013.

[3] Vrushank H. Gandhi ,Sandip R. Panchal , " Feature Based Image Registration Techniques: An Introductory Survey ", International Journal of Engineering Development and Research (IJEDR), Vol. 2, No. 1, pp. 368-375, 2014.

[4] R. Reji and R. Vidya, "Comparative analysis in satellite image Registration", In proceedings of IEEE International Conference on Computational Intelligence & Computing Research (ICCIC), pp. 1-6, 2012.

[5] Guiting Wang, Xiaoxian Liu, Licheng Jiao, Shuang Wang, "A Multiscale Region-Based Approach to Automatic SAR Image Registration using Clpso", In the conference on Geoscience and Remote Sensing Symposium (IGARSS), pp. 5226 – 5229, 2014.

[6] Mahesh, Subramanyam M .V., "Automatic Feature Based Image Registration Using SIFT Algorithm", Third International Conference on Computing Communication & Networking Technologies (ICCCNT), PP. 1 - 5 2012.

[7] S. ManthiraMoorthi, Rajdeep K. Gambhir, IndranilMisra and R. Ramakrishnan, "Adaptive stochastic gradient descent optimization in multi temporal satellite image registration", In proceedings of IEEE Recent Advances in Intelligent Computational Systems (RAICS), pp. 373-377, 2011.

[8] SomoballiGhoshal, Pubali Chatterjee, Biswajit Biswas, AmlanChakrabarti and KashiNathDey, "A novel method for automatic image registration based on wavelet and near fuzzy set", In proceedings of Annual IEEE India Conference (INDICON), 2013.

[9] Ik-Hyun Lee and Tae-Sun Choi, "Accurate registration using adaptive block processing for multispectral images", IEEE Transactions on Circuits and Systems for Video Technology, Vol. 23, No. 9,pp. 1491-1501, 2013.

[10] Zhili Song, Shuigeng Zhou and Jihong Guan, "A Novel Image Registration Algorithm for Remote Sensing Under Affine Transformation", IEEE Transactions on Geoscience and Remote Sensing, Vol. 52, No. 8, pp. 4895-4912, 2014.

[11] Jiayong Liang, Xiaoping Liu, Kangning Huang, Xia Li, Dagang Wang, and XianweiWang. "Automatic registration of multi sensor images using an integrated spatial and mutual information (SMI) metric", IEEE Transactions on Geoscience and Remote Sensing, Vol. 52, No. 1,pp. 603-615, 2014.

[12] Maoguo Gong, Shengmeng Zhao, Licheng Jiao, DayongTian and Shuang Wang, "A novel coarse-to-fine scheme for automatic image registration based on SIFT and mutual information", IEEE Transactions on Geoscience and Remote Sensing, Vol. 52, No. 7,pp. 4328-4338, 2014.

[13] IndranilMisra, S. ManthiraMoorthi, DebajyotiDhar and R. Ramakrishnan, "An automatic satellite image registration technique based on Harris corner detection and Random Sample Consensus (RANSAC) outlier rejection model", In proceedings of IEEE1st International Conference on Recent Advances in Information Technology (RAIT), pp. 68-73, 2012.

[14] K.Priyadharshini, R. R. Jegan, and G. K. D. Venkatesan, "Automatic registration of images with simulated rotation and translation estimation using HAIRIS", In IEEE International Conference on Current Trends in Engineering and Technology (ICCTET), pp. 18-24, 2013.

[15] YoucefBentoutou, NasreddineTaleb, KidiyoKpalma and Joseph Ronsin, "An automatic image registration for applications in remote sensing", IEEE Transactions on Geoscience and Remote Sensing, Vol. 43, No. 9,pp. 2127-2137, 2005.

[16] Hernani Goncalves, Luís Corte-Real and José Gonçalves, "Automatic image registration through image segmentation and SIFT", IEEE Transactions on Geoscience and Remote Sensing, Vol. 49, No. 7,pp. 2589-2600, 2011.

[17] Wong and D. Clausi, "ARRSI: Automatic Registration of Remote-Sensing Images", IEEE Transactions on Geoscience and Remote Sensing, vol. 45, no. 5, pp. 1483-1493, 2007.

[18] Amin Sedaghat and Hamid Ebadi, "Remote Sensing Image Matching Based on Adaptive Binning SIFT Descriptor", IEEE Transactions on Geoscience and Remote Sensing,Vol. 53, No. 10, pp. 1-10, 2015.

[19] Youkyung Han, Jaewan Choi, YounggiByun and Yongil Kim, "Parameter Optimization for the Extraction of Matching Points Between High-Resolution Multisensor Images in Urban Areas", IEEE Transactions on Geoscience and Remote Sensing, Vol. 52, No. 9,pp. 5612-5621, 2014.

[20] Qiaoliang Li, Guoyou Wang, Jianguo Liu and Shaobo Chen, "Robust Scale-Invariant Feature Matching for Remote Sensing Image Registration", IEEE Geoscience and Remote Sensing Letters, vol. 6, no. 2, pp. 287-291, 2009.

[21] Jianglin Ma, Jonathan Cheung-Wai Chan and Frank Canters, "Fully automatic subpixel image registration of multiangle CHRIS/Proba data", IEEE Transactions on Geoscience and Remote Sensing, Vol. 48, No. 7,pp. 2829-2839, 2010.

[22] Tinne Tuytelaars1 and Krystian Mikolajczyk2, "Local Invariant Feature Detectors: A Survey, " Foundations and Trends Rin Computer Graphics and Vision, PP. 177-280, 2008.

[23] P M Panchal, S R Panchal, S K Shah, "A Comparison of SIFT and SURF ", International Journal of Innovative Research in Computer and Communication Engineering, Vol. 1, No. 2, pp. 323-327, 2013.

[24] Luo Juan and Oubong Gwun, "A Comparison of SIFT, PCA-SIFT and SURF", International Journal of Image Processing (IJIP), Vol. 3, No. 4, pp. 187-245, 2009.

[25] Cordelia Schmid, Roger Mohr and Christian Bauckhage, "Evaluation of Interest Point Detectors", International Journal of Computer Vision, pp. 151-172, 2000.

[26] C. Harris and M. Stephens, "A combined edge and corner detector", in 4th Alvey Vision Conference, Manchester, UK, pp. 189-192, 1988.

[27] Zhang Jin-ping, Lian Yong-xiang,Jiao Chun-wang, Guo Da-meng, Liu Jie, "An Improved Harris Corner Distraction Method Based on B_spline", 2nd IEEE International Conference on Information Management and Engineering (ICIME), pp. 504 – 506, 2010.

[28] J Alison Noble, " Finding Corner", Elsevier Image and Vision Computing, Vol. 6, No. 2, pp. 121-128, 1988.

[29] J. Senthilnath, S.N. Omkar, V. Mani, Ram Prasad, Ritwik Rajendra, Shreyas P.B, "Multi-sensor satellite remote sensing images for flood assessment using swarm intelligence", IEEE International Conference on Cognitive Computing and Information Processing (CCIP), pp. 1-5, 2015.

[30] J. Senthilnath, S. N. Omkar, V. Mani, and T. Karthikeyan, "Multi-objective optimization of satellite image registration using discrete particle swarm optimisation", Annual IEEE India Conference (INDICON), pp. 1-5, 2011.

[31] ChahiraSerief, YoucefBentoutou and MouradBarkat, "Automatic Registration of Satellite Images", In proceedings of IEEE First International Conference on Advances in Satellite and Space Communications, pp. 85-89,2009.

[32] Ye Zhang, Yan Guo, Yanfeng Gu, Weizhi Zhong," Particle Swarm Optimization with Powell's Direction Set Method for Multisensor Image Registration", IEEE fifth International Conference on Natural Computation, pp. 388-392, 2009.

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