Feature Based Image Registration Techniques: An Introductory Survey

[1]Vrushank H. Gandhi, [2]Sandip R. Panchal
[1]PG Student, [2]Assistant Professor
[1, 2] Department of Electronics & Communication,
Sardar Vallabhbhai Patel Institute of Technology, Vasad, Gujarat, India
[1]vrushank011@gmail.com, [2] er_sandip79@yahoo.com

***Abstract*— This paper aims to present review of various techniques used for feature based image registration. Image registration is used to combine two or more partially overlapped images and stitch these images into one panoramic image comprising the whole scene. Image registration is very crucial step in all image analysis tasks in which the final information is obtained from the combination of various data sources. Image registration finds its applications in various fields like remote sensing, medical imaging, computer vision and cartography. The reviewed approach is classified according to the four basic steps of feature based image registration: *feature detection, feature matching, transformation function design, and image transformation and resampling.* The advantages and disadvantages of methods are mentioned in this paper. The main goal of the paper is to provide a detailed reference source for the researchers involved in feature based image registration, irrespective of particular application field mentioned above.**

***Keywords*— Image registration, Feature detection, Feature matching, Mapping function, Resampling**

I. INTRODUCTION

Image registration is geometrically aligning two or more images which are sensed from different viewpoints, at different time and/or using the different sensors. Out of these images one is a reference image and all others are called as sensed images. The main idea behind the any image registration algorithm is that the sensed image is undergoes the registration algorithm and its pixel coordinates are converted into the reference image pixel coordinates. In this way we get the transformed sensed image and 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. Depending upon how the images which are to be registered are acquired, the image registration is classified into the four classes.

- Multi view image registration
- Multi temporal image registration
- Multi modal image registration
- Scene to model registration

Multi view image registration (different view points): Images of the same scene are acquired from different viewpoints. Our main aim is to gain larger a 2D view of the scene or a 3D representation of the scanned scene. Examples of applications: Remote sensing: mosaicing of images of the surveyed area. Computer vision: shape recovery.

Multi temporal image registration (different times): Images of the same scene are acquired at different times, often on regular basis, and possibly under different conditions. Here the images which are to be registered are always having the change in illumination because illumination will change as time changes. Our main aim is to find and evaluate changes in the scene which appeared between the consecutive images. Examples of applications: Remote sensing: monitoring of global land usage, planning of landscape. Computer vision: automatic change detection for security monitoring, motion tracking. Medical imaging: monitoring of the healing therapy, monitoring of the tumor growth.

Multimodal modal image registration (different sensors): Images of the same scene are acquired by different sensors. Here the care should be taken that each sensor works on the different frequency bands and hence they sensors the different bands of frequency. Our main aim 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 likes panchromatic images and multispectral images. 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: Images of a scene and a model of the scene are registered. The main difference of this type of registration is here we have one image and another model or map of that image instead of two images like in all above cases. The model can be a computer representation of the scene, for instance maps or digital elevation models (DEM) in GIS, the map showing the amount of vegetation of particular area, the same scene of the another patient with similar content, etc. Our main aim is to localize the acquired image in the scene/model and/or to compare them. Examples of applications: Remote sensing: registration of 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 image with digital anatomical atlases, specimen classification.

For each class of the image registration 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 and feature based methods are used when important information is given by the image features like point, edge, corners, and contours [4].

In Section 2 various steps of feature based image registration are briefly explained. The existing algorithms for feature detection and feature mapping are explained in Section 3 and Section 4 respectively. In Section 5 methods for mapping function design are discussed. Various techniques for image transformation and resampling are described. Finally in Section 6 some basic error criteria for performance evolution are defined.

II. STEPS OF FEATURE BASED IMAGE REGISTRATION

The fundamental steps for the feature based image registration as per B. Zitova and J. Flusser [4] are given in the figure 1.

Feature detection: Any salient and distinctive objects or features like closed-boundary regions, edges, contours, line intersections, corners, etc. are detected using the various feature detectors. For further processing, these features can be represented by their point representatives centre of gravity, line endings, distinctive points which are called control points (CPs).

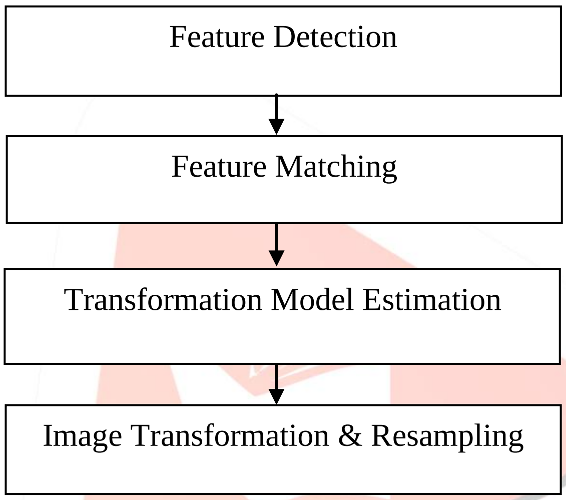

Figure 1: Fundamental steps of feature based image registration [4]

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 matching purpose.

Transformation function design: 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 using the established feature correspondence in the previous step.

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.

Accuracy and performance evaluation: Above four steps completes the image registration. The accuracy of entire image registration algorithm is evaluated based on the parameters like localization error, matching error, alignment error and computational time required.

III. FEATURE DETECTION METHODS

Formerly, features were selected manually by an expert but today lots of automatic feature detection algorithms are available which do not required any human interaction. To detect the various features like point, line, edge, corner, surface from the image different methods are shown in below figure 2.

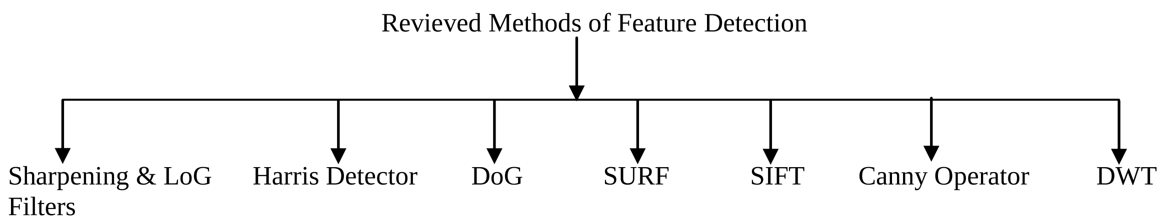

Figure 2: Different methods used for feature detection

Basic sharpening filters

These are basically high pass filters which uses first and second derivatives. The derivatives are used to detect the change in intensity of the image pixels and remove the background where the intensity of the pixels is constant. The advantages of the prewitt and sobel operator are that they both are rotation invariant. Although, these sharpening filters are easy to implement but these require finding the derivatives or gradient of an image in different direction. Obtaining the derivatives of an image is computationally expensive. Another disadvantage is that derivatives are sensitive to the noise.

LoG filters

This filter is second derivative filter with noise cleaning. The noise is first removed using the Gaussian smoothing and then apply second derivative to detect the features from the image. Here noise is removed but still we need to find derivatives of an image which is computationally expensive [10].

Harris corner detector

Harris corner detector is based on the auto correlation function of the signal. The basic idea of this detector is we find whether point shows significant change in all direction or not. If yes then point is marked as a corner point [15]. To do this second moment matrix and corner function is calculated [12, 15, 19, 20]. If both of the Eigen values of the second moment matrix are large and nearly equal than that point are considered as the corner point [15] (see Figure 3). The Harris corner detector is invariant to translation, rotation and illumination change [20]. This detector is most repetitive and most informative. The disadvantage of this detector is it is not invariant to large scale change [19]. Harris detector detects the L-junctions and points with the higher curvature along with the corner points [20]. Here we find the second moment matrix which requires finding the gradients of an image which is sensitive to noise and computationally expensive.

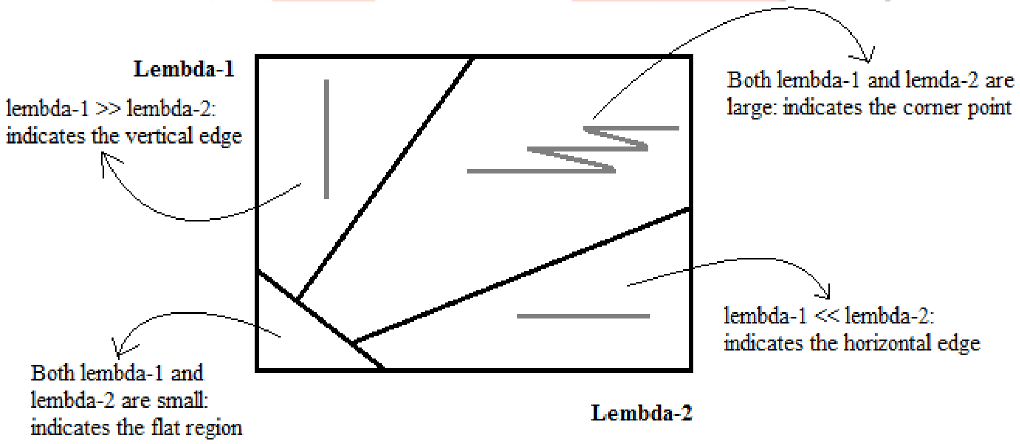

Figure 3: Classification of points using Eigen values of the second moment matrix [15]

There are other modifications are performed on this standard Harris corner detector that gives the better performance in several conditions. Harris - Laplace and Harris - Affine are scale and affine invariant version of it [20].

DoG

All the detectors explained above has common disadvantage that we have to find the derivatives of the images and it is computationally expensive. Laplacian is corresponding to the difference in scale direction. Difference of Gaussian approximates the laplacian without finding derivatives. If we find the difference in particular direction it will give derivative in that direction. Similarly, if we find the difference of the two images having different scales then it will give derivative in scale direction. Hence we have approximated the laplacian without finding the derivatives and therefore this method is computationally less complex [20]. In DoG we blur our image using Gaussian with different scales and then subtraction is performed to obtain the features [20, 11]. Another advantage of DoG is that it is invariant to change in scale [19].

SURF

Speeded Up Robust Features is a scale-invariant feature detector based on the Hessian-matrix, as is, e.g., the Hessian-Laplace detector. However, rather than using a different measure for selecting the location and the scale, the determinant of the Hessian is used for both. The Hessian matrix is roughly approximated, using a set of box type filters, and no smoothing is applied when going from one scale to the next.

Gaussians are optimal for scale-space analysis, but in practice they have to be discretized which introduces artifacts, in particular in small Gaussian Kernels. SURF pushes the approximation even further, using the box filters. These approximate second-order Gaussian derivatives, and can be evaluated very fast using integral images, independently of their size. Surprisingly, in spite of the rough approximations, the performance of the feature detector is comparable to the results obtained with the discretized Gaussians. Box filters can produce a sufficient approximation of the Gaussian derivatives as there are many other sources of significant noise in the processing chain. SURF has been reported to be more than five times faster than DoG [20].

SIFT

Raul Montioliu and Filiberto Pla [8] have used the SIFT technique to detect the features and performed the registration and concluded that the method gives very accurate registration results even when there is an illumination changes, different blur levels, different jpeg compressions, large change of scale and rotations, moderate change of viewpoints. The registration performed using this technique is capable of handling the difference in spectral content, rotation, scale, translation, different viewpoints and change in illumination [18]. Although it is having lots of advantages but its performance is degraded for textured scene or when the edges are not reliable [19]. In remote sensing application like building detection, if there is a low contrast between roof top of the buildings and back ground then SIFT alone cannot be used [19].

Canny edge detector

The Canny edge detector algorithm is actually first order derivative coupled with the noise cleaning. L.Y. Hsu and M.H. Loew [2] authors have find the edges using 3D canny edge algorithm and then by applying automatic segmentation algorithm, the surface is extracted as a feature. Finally, the fully automatic 3D feature based registration for multimodality medical images is performed successfully. Jignesh N Sarvaiya, SupravaPatnaik, Kajal Kothari [3] have used canny edge detection algorithm in their registration and concluded that it is robust against rotation and translation. Akram Bennour, Bornia Tighiouart [16] have used the canny edge detector algorithm to perform curvature based feature detection and obtained the initial edge contours.

Wavelet based feature detection

This method is basically a multi resolution approach. The basic idea of using multiple resolutions is a feature in an image may go undetected at one resolution and the same feature may be easily detected at another resolution. The image is having the features like small in size or low in contrast then we required fine resolution to detect them. The image is having the large or high contrast feature then coarse resolution is sufficient. In reality, the image can have all type of feature in it and hence it is advantageous to analyze the image at different levels of resolution. Chiou-Ting Hsu, Rob A. Beuker [1] have used multi resolution approach to detect the features from the image and concluded that the transformed based method is very much accurate but slowdown the speed of the algorithm. The numbers of problems are existing when we want to perform the registration of the high resolution images [7]. The problems like increased relief displacements, precisely locating the CPs in high resolution image is not the simple task, large number of CPs are required and high data volume often affects the processing speed in image registration. As a conclusion the author found that this method works well for high resolution image. Basically, the wavelet transform decompose the original image in the four sub band images and they are LL, HL, LH and LL.

IV. FEATURE MATCHING METHODS

Once the features from the reference and sensed image are detected the very next step is to find the correspondence between the detected features. In feature matching step, our goal is to find that which feature of the reference image is corresponding to which feature of the sensed image.

Normalized cross correlation method

The classical representative of the feature matching methods is the normalized CC. This measure of similarity is computed for window pairs from the sensed and reference images and its maximum is searched [15]. 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 rotation and scaling 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.

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.

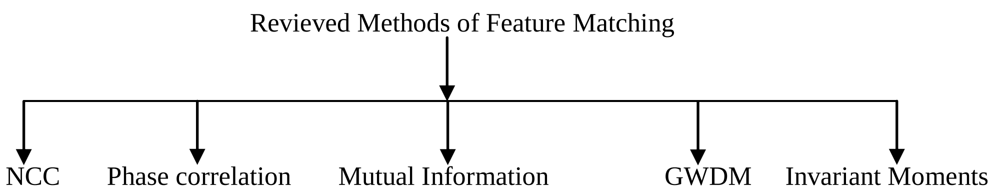

Figure: 4 Reviewed methods for feature matching step

Phase correlation

If an acceleration of the computational speed is needed or if the images were acquired under varying conditions or they are corrupted by frequency-dependent noise, then Fourier methods are preferred rather than the correlation-like methods. They exploit the Fourier representation of the images in the frequency domain. The phase correlation method is based on the Fourier Shift Theorem and was originally proposed for the registration of translated images. It computes the cross-power spectrum of the sensed and reference images and looks for the location of the peak in its inverse. The method shows strong robustness against the correlated and frequency dependent noise and non-uniform, time varying illumination disturbances. The computational time savings are more significant if the images, which are to be registered, are large.

Mutual information method

The mutual information (MI) based methods have appeared recently and represent the leading technique in multimodal registration [4]. Registration of multimodal images is the difficult task, but often necessary to solve, especially in medical imaging. The comparison of anatomical and functional images of the patient’s body can lead to a diagnosis, which would be impossible to gain otherwise. Remote sensing often makes use of the exploitation of more sensor types, too. The MI, originating from the information theory, is a measure of statistical dependency between two data sets and it is particularly suitable for registration of images from different modalities. MI between two random variables X and Y is given by;

$$\begin{aligned} MI(X,Y) &= H(Y) - H(Y \mid X) \\ &= H(X) + H(Y) - H(X,Y) \end{aligned}$$

The method is based on the maximization of MI. Often the speed up of the registration is implemented, exploiting the coarse-to-fine resolution strategy.

GWDM

Ho Lee, Jeongin Lee, Namkug Kim, Sang Joon Kim, Yeong Gil Shin [10] have used Gaussian weighted distance map to find the similarity between the extracted features of the reference and sensed image. As a conclusion, the method gives best alignment even if the features of the reference and sensed images are mismatched. Generally, PET and CT images have always mismatching between the detected features. This method aligned the images robustly even in case where conventional methods cannot be used. The computational time is depending upon the size of GW mask. The higher size of mask will increase the computational time. The accuracy of this method is comparable to that of the MI-based image registration method [10]. As described earlier the main advantage of this method is, it gives the best matching even in presence of localization error.

Moment invariants method

J. Sarvaiya and Dr. Suprava Patnaik [11] have employed the invariant moments to match the features of reference and sensed image. For each detected feature, seven moment invariants vector are calculated.

$$\begin{aligned}
&\varnothing_1 = \eta_{20} + \eta_{02} \\
&\varnothing_2 = (\eta_{20} + \eta_{02})^2 + 4\eta^2_{11} \\
&\varnothing_3 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{21} + 3\eta_{03})^2 \\
&\varnothing_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
&\varnothing_5 = (\eta_{30} + 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\varnothing_6 = (\eta_{20} - \eta_{02})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
&\varnothing_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + \\
&\qquad (3\eta_{12} + \eta_{30})(\eta_{21} + \eta_{03})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned}$$

For one vector of reference image, all the moment vectors of the sensed image are compared. Then by applying minimum distance rule corresponding feature points are extracted. The Hu’s seven moment invariants are calculated using the formula given. Using this method we can register the images having the any degree of rotation [11].

V. TRANSFORMATION FUNCTION DESIGN

Once the set of matched feature (CPs) is obtained, our next task is to select the transformation function or also called as mapping function. Sometimes the RANSAC (Random Sample Consensus) [8, 15] or MDSAC [14] (which is advancement of the RANSAC) algorithms are used to remove the outliers present after the matching step and hence robustness of the algorithm is increases. Outliers are the falsely matched feature. If outliers are not removed it might affect the overall accuracy of the algorithm. After removing the falsely matched feature's pair, the available final set of CPs are called as pruned CPs.

Once the feature correspondence has been established the mapping function is constructed. It should able to transform the sensed image to overlay it over the reference image. One should choose the type of mapping function (see Figure 5) and then one has to find the parameters of the selected mapping function. The selection of the mapping function depends on the geometric deformation of the sensed image. In special situations when the geometric deformation is partially known, e.g. when there exists a model for the distortion caused by the acquisition device and/or the scene geometry, the pre-correction based on the inverse of the deformation can be performed. Models of mapping functions can be divided into two broad categories according to the amount of image data they use as their support. Global models use all CPs for calculating one set of the mapping function parameters valid for the entire image. The local mapping functions treat the image as a composition of patches and the function parameters depend on the location of their support in the image.

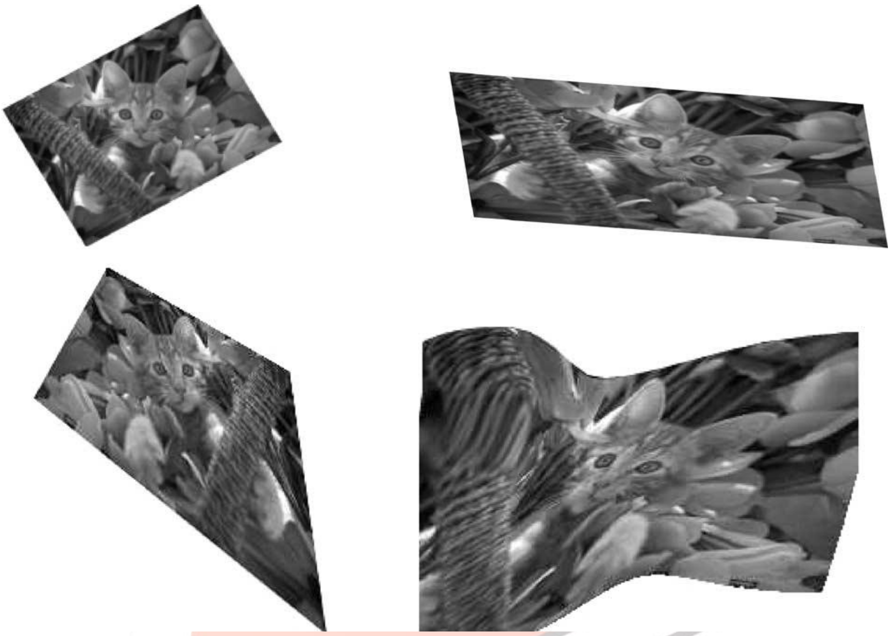

Figure 5: Examples of various mapping functions: similarity transform or rigid planner transform (top left), affine transform (top right), perspective projection (bottom left), elastic transform (bottom right) [4]

Global mapping models

The simplest and rapidly used global mapping model is similarity transform. This model consists of scale, rotation and translation. This mapping model can be solved by using two pairs of CPs. This model preserves the angles and curvatures and hence it is also called as shape-preserving mapping model. This model is also called as rigid planner transform. This mapping model is used when the two images are taken from the same viewing angle but from the different position that is camera can rotate about its optical axis [1].

The transformed coordinate (u, v) is determined from the original coordinate (x, y) as;

$$u = s\,(x \cos(\Theta) - y \sin(\Theta)) + t_x$$
$$v = s\,(x \sin(\Theta) - y \cos(\Theta)) + t_y$$

Slightly more general and linear model is affine transform. This mapping model is used to convert the parallelogram into a square. This mapping model can be solved by using three pairs of CPs. The affine transformation is generally used in multi view image registration where we assume that the distance of the camera is large as compared to the scanned scene. This model exactly describes the deformation of a flat scene photographed by a pin-hole camera having its optical axis is perpendicular to the scene.

$$u = a_0+a_1x+a_2y$$
$$v = b_0+b_1x+b_2y$$

If the distance of the camera to the scene is not sufficient corresponding to the size of the scene then the perspective projection model is used. This mapping model is used to convert the quadrangle into a square. This mapping model can be solved by using four pairs of CPs. This model exactly describes the deformation of a flat scene photographed by a pin-hole camera having its optical axis is not perpendicular to the scene.

$$u = \frac{a0+a1x+a2y}{1+c1x+c2y} \qquad v = \frac{b0+b1x+b2y}{1+c1x+c2y}$$

Chiou-Ting Hsu, Rob A. Beuker has used the projective transformation to solve the deformation between the reference and sensed image. In addition to this they have used the rigid planner transform to make a good initial guess for the projective transformation [1]. L.Y. Hsu and M.H. Loew have used the geometric transformation with the iterative closest point searching algorithm to solve the geometric distortion between two images [2]. Youcef Bentoutou, Nasreddin Taleb, Kidiyo Kpalma, Joseph Ronsin has used the affine transformation coupled with the consistency check to determine the deformation between the two images [5]. Raul Montioliu and Filiberto Pla have estimated the motion (deformation) between two images using GLS motion estimator and RANSAC as the good initial guess [8]. J. Sarvaiya and Dr. Suprava Patnaik have solved the geometric difference bet two images by using the radon transformation and concluded that it can able to solve any degree of rotation [11]. LEI Huang has used the affine transformation to align the reference image and sensed image [12]. Alexander Wong and David A. Clausi have used the DLT algorithm to estimate the final transformation model to align the two images [14]. Akram Bennour and Bornia Tighiouart have used rigid planner transformation for multi temporal satellite image registration [16].

Local mapping model

The global mapping function cannot be used when the image is deformed locally. This is the very often in case of the medical image registration. The least square method averages out the local geometric distortion equally over the whole image which is not desirable. Local areas of the image should be registered with the available information about the local geometric distortion keep in mind.

Gang Hong and Yun Zhang have said that the global mapping function cannot be used for the high resolution remote sensing images where generally off-nadir mode is used to capture the images. Here the triangle based local transformation is used as the mapping function to reduce the local geometric distortion caused by terrain relief [7].

VI. IMAGE TRANSFORMATION AND RESAMPLING

The mapping functions constructed during the previous step 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, called a forward method, is complicated to implement, as it can produce holes and/or overlaps in the output image (due to the discretization and rounding). Hence, the backward approach is usually chosen.

The registered image data from the sensed image are determined using the coordinates of the target pixel (the same coordinate system as of the reference image) 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. In order to reduce the computational cost, preferably separable interpolants have been considered. The separability enables to replace an m x m 2D convolution by 1D convolution which is much faster. B. Zitova and J. Flusser have reviewed that most generally used interpolation techniques are bilinear interpolation and nearest neighbor interpolation [4]. Bentoutou, Nasreddin Taleb, Kidiyo Kpalma, Joseph Ronsin have used TPS (Thin Plate Spline) interpolation to warp the sensed image into the coordinate of the reference image for the application of remote sensing [5]. LEI Huang has used the TPS (Thin Plate Spline) interpolation technique to warp the sensed image into the coordinate of the reference image for airborne optical and SAR images [12].

VII. ACCURACY AND PERFORMANCE EVOLUTION

Regardless of the particular images, the used registration method, and the application area, it is highly desirable to provide the user with an estimate how accurate the registration actually is. The accuracy evaluation is a nontrivial problem, partially because the errors can be dragged into the registration process in each of its stages and partially because it is hard to distinguish between registration inaccuracies and actual physical differences in the image contents. In this Section, we review basic error classes and methods for measuring the registration accuracy.

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 trade-off 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.

Matching error: Matching error is measured by the number of false matches when establishing the correspondence between CP candidates. 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.

Alignment error: Alignment error is denoted by the difference between the mapping model used for the registration and the actual 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 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 their localization errors.

VIII. REFERENCES

[1] Chiou-Ting Hsu, Rob A. Beuker, "Multiresolution Feature Based Image Registration," Visual Communication and Image Processing, June 2000.

[2] L.-Y. Hsu*, M.H. Loew, "Fully automatic 3D feature based registration of multi-modality medical images," Elsevier Image and computing, June 2000.

[3] Jignesh N Sarvaiya, SupravaPatnaik, Kajal Kothari, "Feature based image registration using houghtransform," IJSCET, July 2012.

[4] B.Zitova, J. Flusser, "Image Registration Methods: a survey," Elsevier Image and Vision Computing, July 2003.

[5] Youcef Bentoutou, Nasreddin Taleb, Kidiyo Kpalma, Joseph Ronsin, "An Automatic Image Registration for Application in Remote Sensing," IEEE Transactions on Geoscience and Remote Sensing, September 2005.

[6] O.Cardon, S. Damas, Santamaria, "Feature based registration by means of the CHC evolutionary algorithm", Elsevier Image and Vision Computing, February 2006.

[7] Gang Hong, Yun Zhang, "Wavelet Based IR tech. for high resolution Remote Sensing images," Computers & Geosciences , March 2008.

[8] Raul Montioliu, Filiberto Pla, "Accurate Image registration by combining feature-based matching and GLS-motion estimation," Spanish CICYT, March 2007.

[9] Gong-jian Wen, "A High-Performance Feature Matching Method for IR by Combining spatial and Similarity Info.", IEEE Transactions on Geosciences and Remote Sensing, April 2008.

[10] Ho Lee, Jeongin Lee, Namkug Kim, Sang Joon Kim, Yeong Gil Shin, "Robust feature-based registration using a Gaussian-weighted distance map and brain feature points for brain PET/CT images", Elsevier Computers in Biology and Medicine, April 2008.

[11] J. Sarvaiya, Dr. Suprava Patnaik, "Automatic Image Registration Using Mexican Hat Wavelet, Invariant Moments and Radon Transform", IJACSA, special Issue on Image Processing and Analysis, July 2010.

[12] LEI Huang, "Feature –based image registration using the shape context," International Journal of Remote Sensing, June 2010.

[13] Francisco Eugeni, Ferran Marquésand Javier Marcello, "A contour-based approach to automatic and accurate registration of multi temporal and multi sensor satellite imagery," IEEE Transactions on Geoscience and Remote Sensing, May 2007.

[14] Alexander Wong, Student Member, IEEE, and David A. Clausi, Senior Member, IEEE, "ARRSI: Automatic Registration of Remote-Sensing Images", IEEE Transactions on Geoscience and Remote Sensing, May 2007.

[15] Indranil Misra, S. Manthira Moorthi, Debajyoti Dhar and R. Ramakrishnan, (ISRO) Ahmedabad 380015, India, "An Automatic Satellite Image Registration Technique Based on Harris Corner Detection and Random Sample Consensus (RANSAC) Outlier Rejection Model", 1st Int'l Conf. on Recent Advances in Information Technology, RAIT-2012.

[16] Akram Bennour, Bornia Tighiouart, "Automatic High Resolution Satellite Image Registration by Combination of Curvature Properties and Random Sample Consensus", 6th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT), 2012.

[17] Reji R, Vidya R, "Comparative Analysis in Satellite Image Registration", ICCIC, July 2012.

[18] Hernâni Gonçalves, Luís Corte-Real, Member, IEEE, and José A. Gonçalves, "Automatic Image Registration Through Image Segmentation and SIFT", IEEE Transactions on Geoscience and Remote Sensing, July 2011.

[19] Cordelia Schmid, Roger Mohr and Christian Bauckhage, "Evaluation of Interest Point Detectors," International Journal of Computer Vision, June 2000.

[20] Tinne Tuytelaars1 and Krystian Mikolajczyk2, "Local Invariant Feature Detectors: A Survey," Foundations and Trends Rin Computer Graphics and Vision, May 2008.

[21] Medha V. Wyawahare, Dr. Pradeep M. Patil, and Hemant K. Abhyankar, "Image Registration Techniques: An overview," International Journal of Signal Processing, Image Processing and Pattern Recognition, September 2009.