Scientific Journal of Impact Factor (SJIF): 4.72
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 4, Issue 12, December -2017

PRECISE IMAGE REGISTRATION BASED ON SIFT WITH RANSAC ALGORITHM

M.Uday kumar[1], Shaik Taj Mahaboob[2]

P G Scholar, Department of ECE, JNTUA College of Engineering (Autonomous), Pulivendula[1]
Assistant Professor, Department of ECE, JNTUA College of Engineering (Autonomous), Pulivendula[2]

Abstract—*This paper discussesThe automatic image registration of oblique images taken at different viewpoints remains a challenge until today. Image registration is the process of geometrically aligning two images taken at different times, at different orientations, or by different sensors. It is vital step in image analysis. It has wide range of applications in the field of satellite imaging, and several medical as well as computer vision fields. Image registration is the fundamental task used to match two or more images of same scene taken at different environments. The steps in image registration consist of feature point detection, feature point descriptor extraction and feature point matching. The main aim of the matching is to find the correspondence between the two images. For the process of image matching extraction of stable features (key points) is the major issue. Generally corner detectors used as stable features, apart from the corners some region based detectors are there. One of the region based detector is Scale Invariant Feature Transform (SIFT) algorithm. SIFT is one of the feature point detectors that can able to provide a set of features of an image that are not affected by many of the complications experienced in other methods. Random Sample Consensus (RANSAC) algorithm is applied to eliminate variety of mismatches and acquire transformation matrix between the images. The input image transformed with the right mapping model for image mosaic. Image mosaic is combining or stitching several images of a same scene or object taken from different angles into a single image with large field of view. In this work, an algorithm for mosaicing of two images efficiently using SIFT feature detection method. The false matching pair is removed by using RANSAC algorithm. The transformation model estimated from the features and the image warped correspondingly.*

Key words—*Scale Invariant Feature Transform, Random sample consensus, Image Mosaicing.*

I. INTRODUCTION

The feature based methods do not directly work with image intensity values. But instead, use salient features extracted from two images, which has been shown to be more suitable for such situations that intensity changes and complicated geometric deformations are encountered. A method for extracting the distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene. The features are invariant to image scale and rotation, and are shown to provide robust matching across a substantial range of affine distortion, change in viewpoint, addition of noise, and change in illumination

1.1 Scale Invariant Feature Transform

Scale-invariant feature transform (SIFT) is an algorithm developed by D.G Lowe. This algorithm is meant for both detection and description of local features of the image. This algorithm detects the features are of outmost accurate and stable. The procedure of SIFT mainly includes three steps: keypoint detection, descriptor establishing, and image feature matching

1.2 Image Matching

Image matching is the fundamental issue in computer vision. . By observing the two images that which are considered, the difficulty in finding the correspondence between the images arises when the images are different environments i.e. different view, different scale & rotation, and different illumination. Image matching can be categorized as gray-scale based matching or image feature based matching. Feature-based matching finds some features within the images such as points, lines, surfaces, planes, and then defines properties of those features and then matches the image according to these characteristics. Key region or point of interest is often used as the local feature due to its stable performance in detection and description. The local features can be derived from a circle or ellipse with certain location and radius, these types of keypoints are effective and efficient when compared with other type of features such as edges. Therefore, these kinds of key points were extensively used in real time applications because of their stability in various environments (view change, scale, rotation, illumination variation).

In block diagram mainly consists of three blocks namely SIFT, RANSAC and image mosaic. In the above block diagram, where SIFT, RANSAC and image mosaic together is used to determine the corresponding points in the overlapping areas of both the images. These corresponding points define the underlying transformation matrix between the frames. The number of matched keypoints obtained by the SIFT is very large which increases the complexity of the registration algorithm. In order to solve this problem an algorithm for image registration that combines SIFT, RANSAC and image mosaic is proposed.

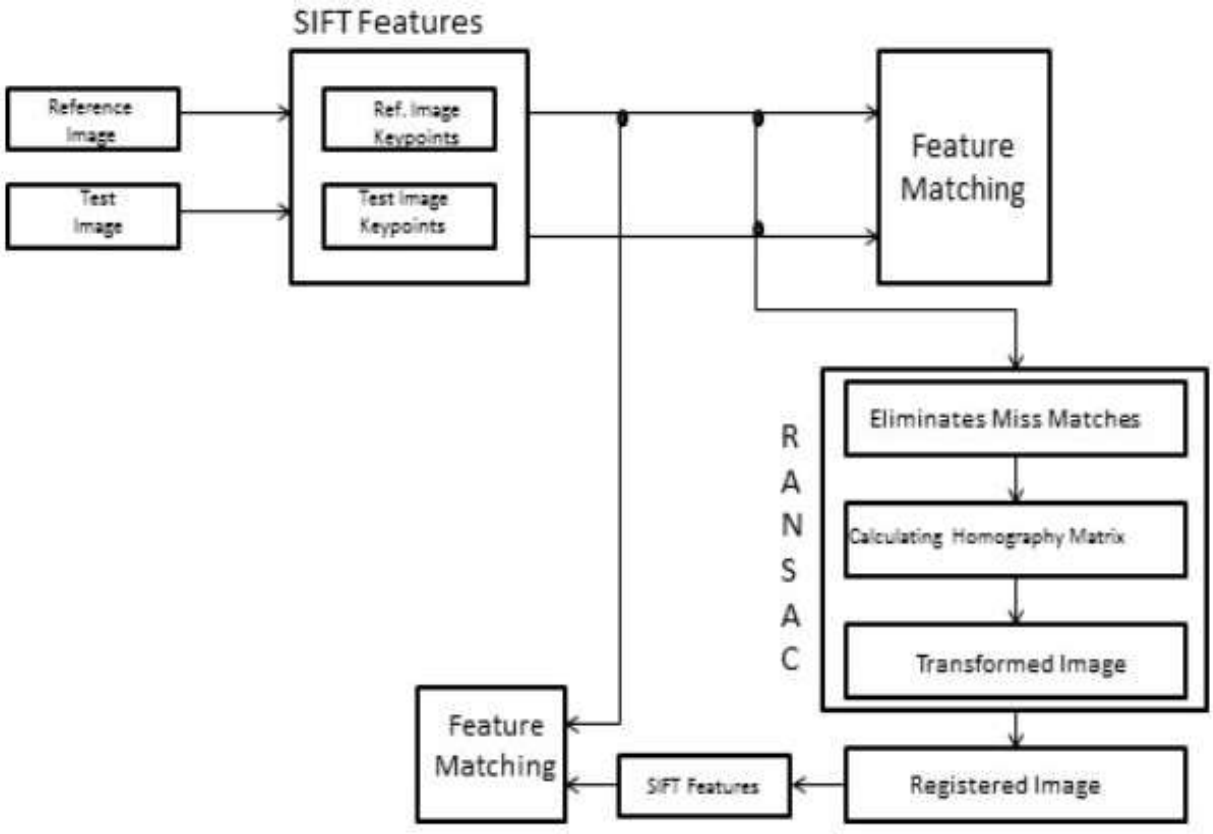

Figure 1: Block Diagram of Image Registration

Using RANSAC the outlier elimination is done. And calculate the transformation matrix H it gives the relationship between the two image corresponding points. Numbers of keypoints are matched based on the keypoint location. It is called as homography, then in order to create a new image with the same feature points as reference image by using projective transformation. Image warping of the input image can be performed by transformation model. The geometrical transformation of the two images are done by using image warping and mosaicing.

$$matching\ percentage = \frac{number\ of\ matches\ found}{total\ number\ of\ keypoints}$$

II. IMAGE REGISTRATION SYSTEM

2.1 Scale Invariant Feature Transform

Scale Invariant Feature Transform termed as SIFT is used to identify locations and scales that can be repeatedly assigned under different views of the same object. SIFT has five computational phases as shown in the Figure 3.2. This includes scale space extrema detection, difference of Gaussian, keypoint localization, orientation assignment and keypoint descriptors.

2.1.1Flow chart

The flowchart of SIFT algorithm is interpreted in Figure 2.

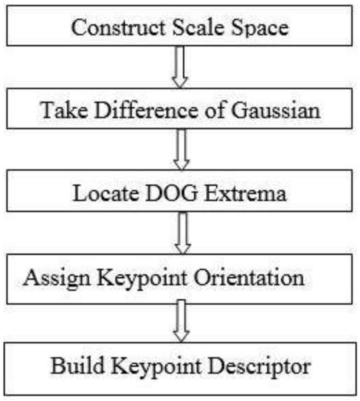

Figure 2: SIFT feature detection algorithm

2.1.2 Detection of Scale Space Extrema

This theory of scale space is used to detect the keypoints which are also known as points of interest. The scale space using a difference of Gaussian (DOG) function to identify potential interest points that can be invariant to scale and orientation. The scale space of an image is defined as a function L(x, y, σ), which is produced from the convolution of variable- scale Gaussian G(x, y, σ) with an input image I(x, y).

The scale space is represented by using the Equation 2.1

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \qquad (2.1)$$

I(x, y) - input image

G(x, y, σ) - Gaussian filter, σ- scale

Where $G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} exp\{-(x^2 + y^2)/2\sigma^2\}$

To efficiently detect stable keypoint locations in scale space using scale space extrema in the DOG[5] function convolved with the image, D(x, y, σ) which can be computed from the difference of two nearby scales separated by a constant multiplicative factor k.

DOG can be represented using the Equation 2.2

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \qquad (2.2)$$

Where k- Constant multiplicative factor

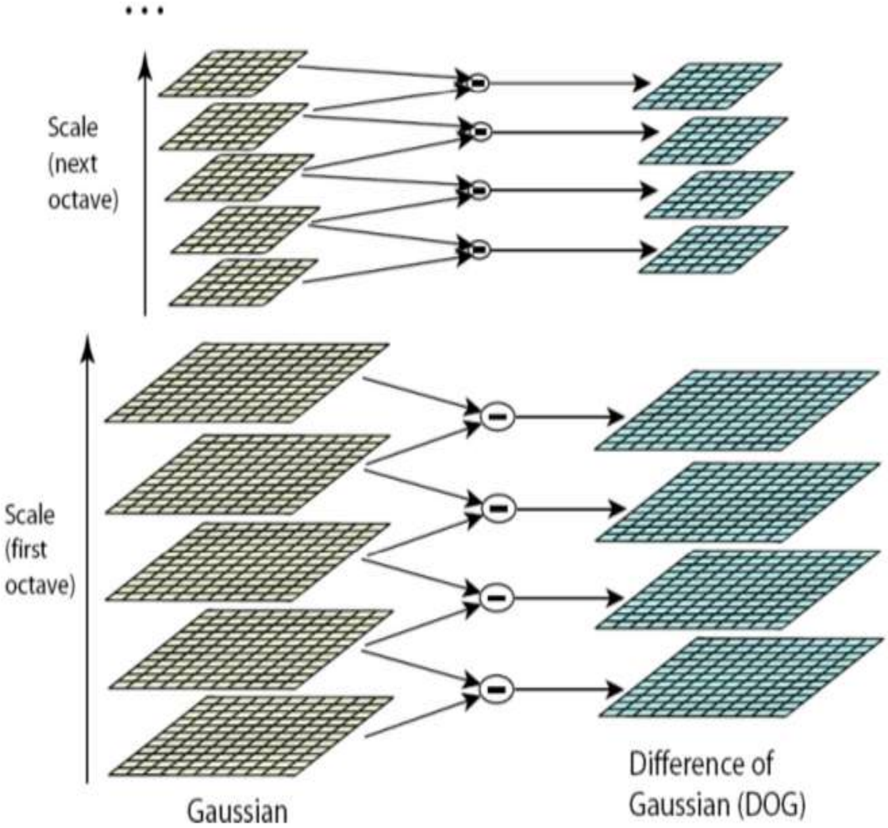

Figure 3: DOG at varying octave

International Journal of Advance Engineering and Research Development (IJAERD)
Volume 4, Issue 12, December-2017, e-ISSN: 2348 - 4470, print-ISSN: 2348-6406

2.1.3 Keypoint Localization

In this method, local maxima or local minima are regarded as keypoints. After tracking the DoG only the keypoints were selected. The keypoint is known as local maxima when each pixel is compared with the eight neighboring pixels of same scale. By using the Taylor series expansion, the local extreme points and their location are carefully stated

The Taylor expansion of DoG is as represented by Equation 2.3.

$$D(X) = D + \frac{\partial D^T}{\partial X} X + \frac{1}{2} X^T \frac{\partial^2 D}{\partial X^2} X \quad (2.3)$$

2.1.4 Orientation Assignment

Here, every keypoint is having one or more orientations defending on the local image gradient directions. This step helps in achieving invariance to rotation because the keypoint descriptor can be presented relative to this orientation and thus invariance to image rotation is achieved

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2} \quad (2.4)$$

$$\theta\,(x, y) = \arctan\,((L(x, y+1)-L(x, y-1))/(L(x+1, y)-L(x-1, y))) \quad (2.5)$$

Where (x, y)are the coordinates of a pixel in Gaussian smoothed image

The computation of magnitude and direction for gradient are done at every pixel in the neighbouring region around the candidate keypoint in the Gaussian-blurred image. An orientation histogram of 36 bins is created, with each been having 10 degrees. Lowe's extensive experiments demonstrate that the SIFT features are resistant to even large amount of pixel noise, and the major cause of error is the initial location and scale detection For multiple orientations, an additional keypoint is created which have the same location and scale as that of the original keypoint for each additional orientation. Each sample of the neighbouring window is added to the histogram bin which is weighted by its gradient magnitude also by a Gaussian-weighted circular window with 1.5 time σ to the scale of the candidate keypoint.

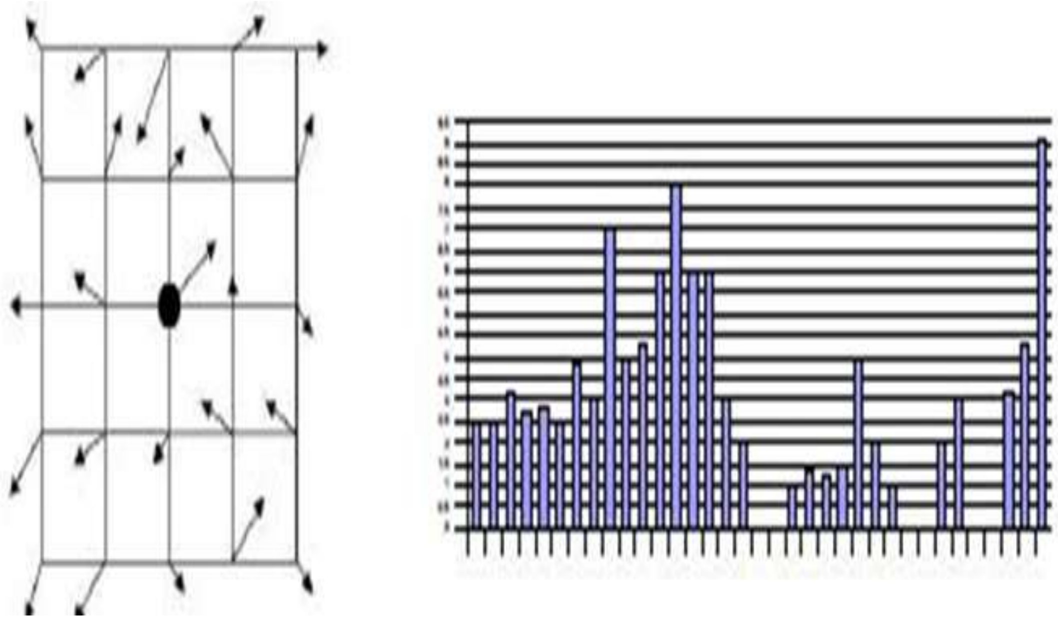

Figure 4: orientation assignment; Left: The point in the middle is the keypoint. The orientations of the points in the square area around this point are pre-comutesd using pixel difference. Right: The value of each bin holds the magnitude sums from all the points pre-computed within that orientation

2.1.5 Keypoint Descriptor Generation

This step insures invariance to image location, scale and rotation. Now compute a descriptor vector for every keypoint such that the descriptor is highly distinctive and partially invariant to the variations such as accuracy, illumination 3D viewpoint, stability etc. This step is performed on the image scale which is closest in scale to the scale of the keypoint.

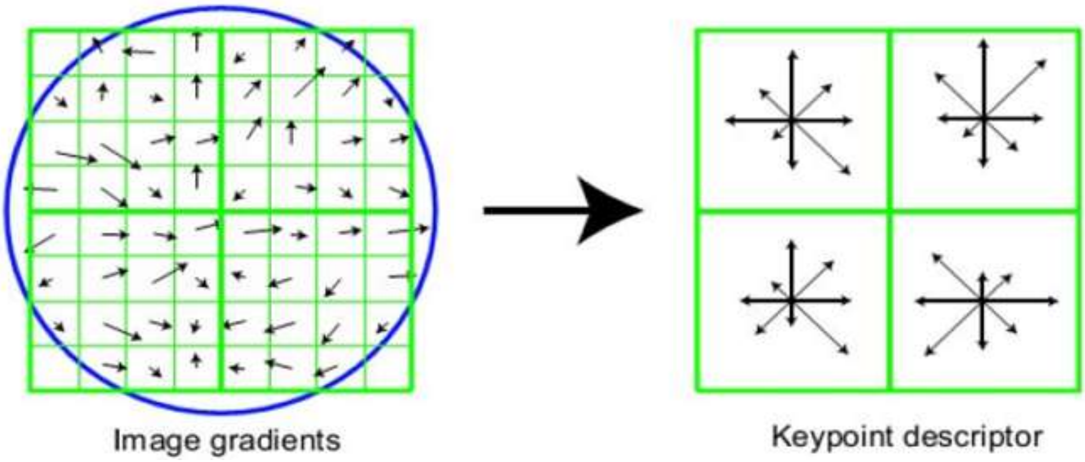

Figure 5: Generation of feature vector

2.2 Random Sample Consensus (RANSAC) Algorithm

The Random Sample Consensus (RANSAC) algorithm proposed by Fischer and Bolles is a general parameter estimation approach designed to cope with a large proportion of outliers in the input data. Unlike many common robust estimation techniques such as M-estimators and least-median squares that have been adopted by the computer vision community from within the computer vision community. RANSAC algorithm input consists of set of observed data and a parameterized mathematical model which can fit to the observations or observed data, along with some confidence parameters. The idea of algorithm is simple; for a number of iterations, a random sample of four correspondences is selected and a homogarphy H is computed from those four correspondences. Each other correspondence is then classified as an inlier or outlier depending on its concurrence with H. after all of the iterations are done; the iteration that contained the largest number of inliers is selected. H can then be recomputed from all the correspondence that we are considered as inliers in that iteration. One important issue when applying the RANSAC algorithm describe above is to decide how to classify correspondence as inliers or outliers. Statistically speaking, the goal is to assign a distance threshold, such that with a probability α point is an inlier. Then the algorithm as follows:

1. Randomly choose minimal subset of points necessary to fit model.
2. Points with some distance threshold t of model are consensus.
3. Repeat for N iterations: model with biggest support is most robust fit.
4. Points within distance t of best model are inliers.
5. Fit final model for to all inliers.

$$1 - p = ((1 - (u)^m))^N (2.6)$$

$$N = \frac{\log(1-p)}{(\log(1-(1-(v)^m)))} \quad (2.7)$$

Where,

u - Represents the probability that any selected data points is an inlier.

v = 1-u the probability of observing outlier.

N – Number of iteration

m – Minimum number of points.

Chose the homography with the largest consensus set and use that consensus set to re-estimate the homography H using least squares

2.2.1 Homography Computation

To work in homogeneous coordinates, there should be relationship between the coordinate points which we are dealing with. The points might be image features such as SIFT feature descriptors. The transformation in between the images can be achieved by finding homography in between these points that which provides the maximum number of inliers. Any of the four pointsX', X which are homogeneous are expressed as shown below Equation

$$X' = HX$$

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}$$

And $$X' = [x' \quad y' \quad 1]$$
$$X = [x \quad y \quad 1]$$

With this transformation the test image is transformed like the reference image. In this transformation involved with respect to particular keypoint location is calculated as H and it provide the entire information about the transformation involved by the test image with respect the reference image

2.2.2 Image mosaic

The mosaic image is the process of aligning two or more images in order to obtain a single image. After the appropriate transformation has been applied, images are warped and the overlapping area of warped images is merged into a common surface which gives the single indistinguishable image which is amount version of a single large image of the same scene. The resultant image is the motivation for image mosaicing.

III. RESULTS AND DISCUSSION

3.1 Evaluation Process

The evaluation of the implemented registration system is made by testing it over wide range of images with varying environments from the database provided by Mikolajczyk. This database consists of 7 different set of images portraying a different environments (1.Graffiti (view change) 2.Wall (view change) 3.Boat (scale and rotation) 4. Bark (scale and rotation) 5.Leuven (illumination) 6. Bike (blur) 7. Tree (blur)) they are each set has 6 images from which one image is taken as reference image and remaining are used as test images to be registered.

A (Reference Image)	B (Test image 1)	C (Test image 2)	D (Test image 3)	E (Test image4)	F (Test image 5)

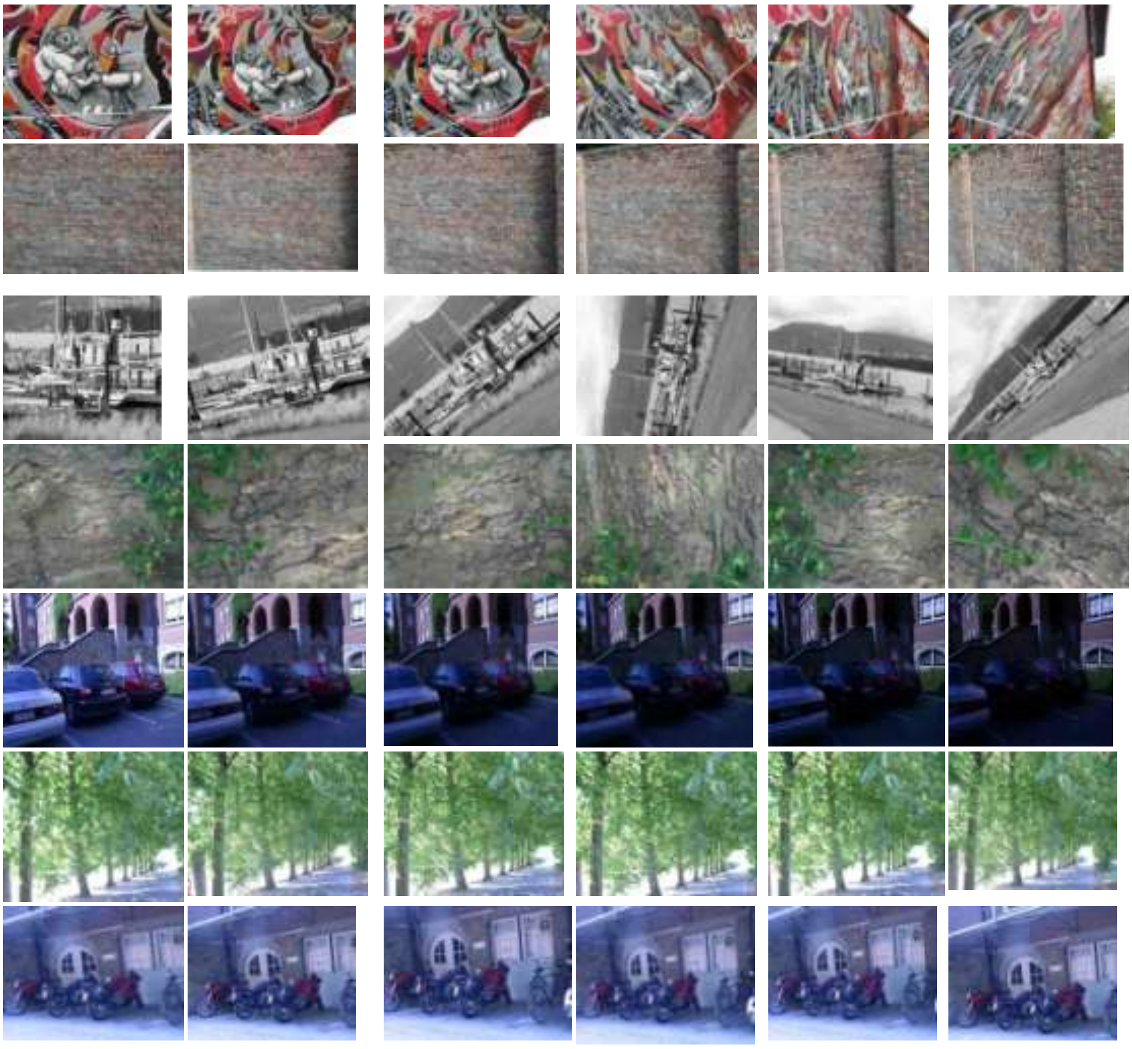

Fig 4.1: Database images; column A represents the Reference images; column B to column F represents the test images. Row 1, row 2 images with view change (Graffiti image, wall image), row 3, row 4 images with scale change and

rotation (boat image, bark image), row 5 image with illumination change (Leuven image); row 6, row 7 represent blur images (bikes image, trees image).

Table 4.3. Performance comparison of the registration system with respect to the images in different environments

	Ref. image No .of keypoints	No .of keypoints for Test image with highest matching percentage	Matching percentag e using SIFT	Transformed image No .of keypoints (SIFT+RANSAC)	Matching percentage (SIFT+RANSAC)	Registered image No. of keypoints (SIFT+RANSAC with mosaic)	Implemented method matching percentage (SIFT+RANSAC with mosaic)
Graffiti	3094	3982	14.83	4720	40.27	2900	93.72
Wall	10612	11860	54.22	15826	52.02	10483	98.78
Boat	9687	5670	12.64	11876	8.423	9589	97.88
Bark	4226	3465	19.01	3142	18.26	4110	95.82
Leuven	2709	1719	46.01	2048	38.62	2655	98.00
Tree	14288	11343	4.42	10705	4.28	14505	98.99
Bike	3825	2015	46.15	1858	46.44	3811	99.76

This matching algorithm is to identification of object with no mismatches even for change in illumination scale & rotation and minor change in viewpoint. This chapter deals with the results and discussion of the implemented system. The figures and tables in this chapter show the matching accuracy obtained for test image used. The images for large variation n view changes SIFT will fails to get the proper matching rate, the failure condition also discussed. In the image registration the matching percentage was increased compared to initial matching and transformed image matching. This matching algorithm is to identification of object with no mismatches even for change in illumination scale & rotation and minor change in viewpoint.

REFERENCES

[1] B. Zitova and J. Flusser, "Image registration methods: A survey," Image Vis. Comput., vol. 21, no. 11, pp. 977–1000, Oct. 2003.

[2] C. Harris and M. Stephens, "A combined corner and edge detection," 1988, pp. 147–151.

[3] D. Lowe, "Distinctive image features from scale-invariant keypoints," Int. J. Comput. Vis., vol. 60, no. 2, pp. 91–110, Nov. 2004.

[4] K. Mikolajczyk and C. Schmid, "Scale & affine invariant interest point detectors," Int. J. Comput. Vis., vol. 60, no. 1, pp. 63–86, Nov. 2004.

[5] J. M. Morel and G. Yu, "ASIFT: A new framework for fully affine invari-ant image comparison," SIAM J. Imag. Sci., vol. 2, no. 2, pp. 438–469,Apr. 2009.

[6] M. A. Fischler and R. C. Bolles, "Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography," pp. 381–395, Jun.1981.

[7] M. Brown and D. G. Lowe, "Automatic panoramic image stitching using invariant features," pp. 59–73,Aug. 2007

[8] J. Yao and W. K. Cham, "Robust multiview feature matching from multi-ple unordered views," Pattern Recognit., vol. 40, no. 11, pp. 3081–3099,Nov. 2007.

[9] Q. L. Li, G. Y. Wang, J. G. Liu, and S. B. Chen, "Robust scale-invariant feature matching for remote sensing image registration," IEEE Geosci. Remote Sens. Lett., vol. 6, no. 2, pp. 287–291, Apr. 2009.

[10] J. M. Morel and G. Yu, ASIFT: A New Framework for Fully Affine Invariant Image Comparison2009. [Online]. Available: http:// www.ipol.im/pub/algo/my_affine_sift

[11]Yang Huachao, Zhang Shubi, and Wang Yongbo "Robust and Precise Registration of Oblique Images Based on Scale-Invariant Feature Transformation Algorithm," IEEE geosciences and remote sensing letters, vol. 9, no. 4, July 2012

[12] Z.Yi Huazhong Univ. Sci. & technol., Wuhan, C. Zhiguo, X.Yang "MultiSpectral Image Registration based on SIFT" IEEE explore digital library Volume: 44 Issue: 2

[13] Ibrahim El rube, Ahmed Salman, Ashor salem "Automatic Selection of Control points for Sensing Image Registration Based on Multi-Scale SIFT". International Conference on Signal, Image Processing and Applications, 2011.

[14] Maoguo Gong, Member, IEEE, Shengmeng Zhao, Licheng Jiao, Senior Member, IEEE, Dayong Tian, and Shuang Wang, Member, IEEE , "A Novel Coarse-to-Fine Scheme for Automatic Image Registration Based on SIFT and Mutual Information"

[15] Youcef Bentoutou, Nasreddine Taleb, Kidiyo Kpalma, and Joseph Ronsin. "An Automatic Image Registration for Applications in Remote Sensing". IEEE Transactions On Geoscience And Remote Sensing, Vol. 43, No. 9, September 2005.