IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676,p-ISSN: 2320-3331, Volume 10, Issue 5 Ver. I (Sep – Oct. 2015), PP 30-37
www.iosrjournals.org

Image registration Analysis

Md Shahid Ullah
(Lecturer, Department of Electrical and Electronic Engineering, International Islamic University Chittagong, Bangladesh)

Abstract : *Image registration is the process of overlaying images (two or more) of the same scene taken at different times, from different viewpoints, and/or by different sensors. The registration geometrically aligns two images (the reference and sensed images). The approaches are classified according to their nature (area based and feature-based) and according to four basic steps of image registration procedure: feature detection, feature matching, mapping function design, and image transformation and re-sampling. Finally we have tested the result of feature detection and feature matching steps by using technique called corner detector and corner matching and also for Scale-Invariant Key points Features (SIFT) detection method. This methods are implemented with MATLAB 2009 .*
Keywords: *feature detection, feature matching, image transformation, image registration.*

I. Introduction

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints and/or by different sensors. It geometrically aligns two images—the reference and sensed images. The present differences between images are introduced due to different imaging conditions. Image registration is a crucial step in all image analysis tasks in which the final information is gained from the combination of various data sources like in image fusion, Change detection, and multichannel image restoration. Typically, registration is required in remote sensing(multispectral classification, environmental monitoring, change detection, weather forecasting, creating super-resolution images, integrating information into geographic information systems (GIS), in medicine(combining computer tomography (CT) to obtain more complete information about the patient, monitoring tumor growth, treatment verification, comparison of the patient's data with anatomical atlases),in cartography (map updating), and in computer vision(target localization, automatic quality control), to name a few. During the last decades, image acquisition devices have undergone rapid development and growing amount and diversity of obtained images invoked the research on automatic image registration. The intention of this report is to discuss the general image registration techniques and applying the Scale Invariant Feature Transform (SIFT) and Curvature Scale-Space (CSS) Corner Detector and a Robust Corner Matching approaches and discussing their performance

II. Literature Review

Image registration, as it was mentioned above, is widely used in remote sensing, medical imaging, computer vision etc. In general, its applications can be divided into four main groups according to the manner of the image acquisition [1].

Different viewpoints (multi view analysis). Images of the same scene are acquired from different viewpoints. The aim is to gain larger a 2D view or a 3D representation of the scanned scene. Examples of applications: Remote sensing and mosaicing of images of the surveyed area. Computer vision—shape recovery (shape from stereo).

Different times (multi temporal analysis). Images of the same scene are acquired at different times, often on regular basis, and possibly under different conditions. The aim 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

Different sensors (multimodal analysis). Images of the same scene are acquired by different sensors. The 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 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 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 model can be a computer representation of the scene, for instance maps or digital elevation models (DEM) in GIS, another scene with similar content (another patient), 'average' specimen, etc. The aim 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

Due to the diversity of images to be registered and various types of degradations it is impossible to design a universal method applicable to all registration tasks. Every method should take into account not only the assumed type of geometric deformation between the images but also radiometric deformations and noise corruption, required registration accuracy and application-dependent data characteristics. Nevertheless, the majority of the registration methods consist of the following four steps [1].

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

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 along with spatial relationships among the features are used for that purpose

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.

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

The methods we are going to discuss also contains this steps

.

III. Scale Invariant Feature Transform (Sift)

This approach transforms an image into a large collection of local feature vectors, each of which is invariant to image translation, scaling, and rotation, and partially invariant to illumination changes and affine or 3D projection. Following are the major stages of computation used to generate the set of image features [8]:

1. Scale-space extreme detection: The first stage of computation searches over all scales and image locations. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and orientation.
2. Key point localization: At each candidate location, a detailed model is fit to determine location and scale. Key points are selected based on measures of their stability.
3. Orientation assignment: One or more orientations are assigned to each key point location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.
4. Key point descriptor: The local image gradients are measured at the selected scale in the region around each key point. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination.

The SIFT features share a number of properties in common with the responses of neurons in inferior temporal (IT) cortex in primate vision. The scale-invariant features are efficiently identified by using a staged filtering approach. The first stage identifies key locations in scale space by looking for locations that are maxima or minima of a difference-of-Gaussian function. Each point is used to generate a feature vector that describes the local image region sampled relative to its scale-space coordinate frame. The features achieve partial invariance to local variations, such as affine or 3D projections, by blurring image gradient locations. This approach is based on a model of the behavior of complex cells in the cerebral cortex of mammalian vision. The resulting feature vectors are called SIFT keys. The current object models are represented as 2D locations of SIFT keys that can undergo affine projection. Sufficient variation in feature location is allowed to recognize perspective projection of planar shapes at up to a 60 degree rotation away from the camera or to allow up to a 20 degree rotation of a 3D object. The Feature detection and matching technique used in the software is described below. To allow for efficient matching between models and images, all images are first represented as a set of SIFT (Scale Invariant Feature Transform) features. Each SIFT feature represents a vector of local image measurements in a manner that is invariant to image translation, scaling, and rotation, and partially invariant to changes in illumination and local image deformations. A typical image will produce several thousand overlapping features at a wide range of scales that form a redundant representation of the original image. The local and multi-scale nature of the features makes them insensitive to noise, clutter and occlusion, while the detailed local image properties represented by the features makes them highly selective for matching to large databases of previously viewed features.

The SIFT feature locations are efficiently detected by identifying maxima and minima of a difference-of- Gaussian function in scale space. At each such location, an orientation is selected at the peak of a histogram of local image gradient orientations. A feature vector is formed by measuring the local image gradients in a region around each location in coordinates relative to the location, scale and orientation of the feature. The gradient locations are further blurred to reduce sensitivity to small local image deformations, such as result from 3D viewpoint change. In summary, the SIFT approach transforms local image features relative to coordinate frames that are expected to be stable across multiple views of an object.

Here we have used the 3D image dataset name solider. Below is the resulted matching output by using the SIFT method. We have several images of the same object so it is a Multi view Image registration designation.

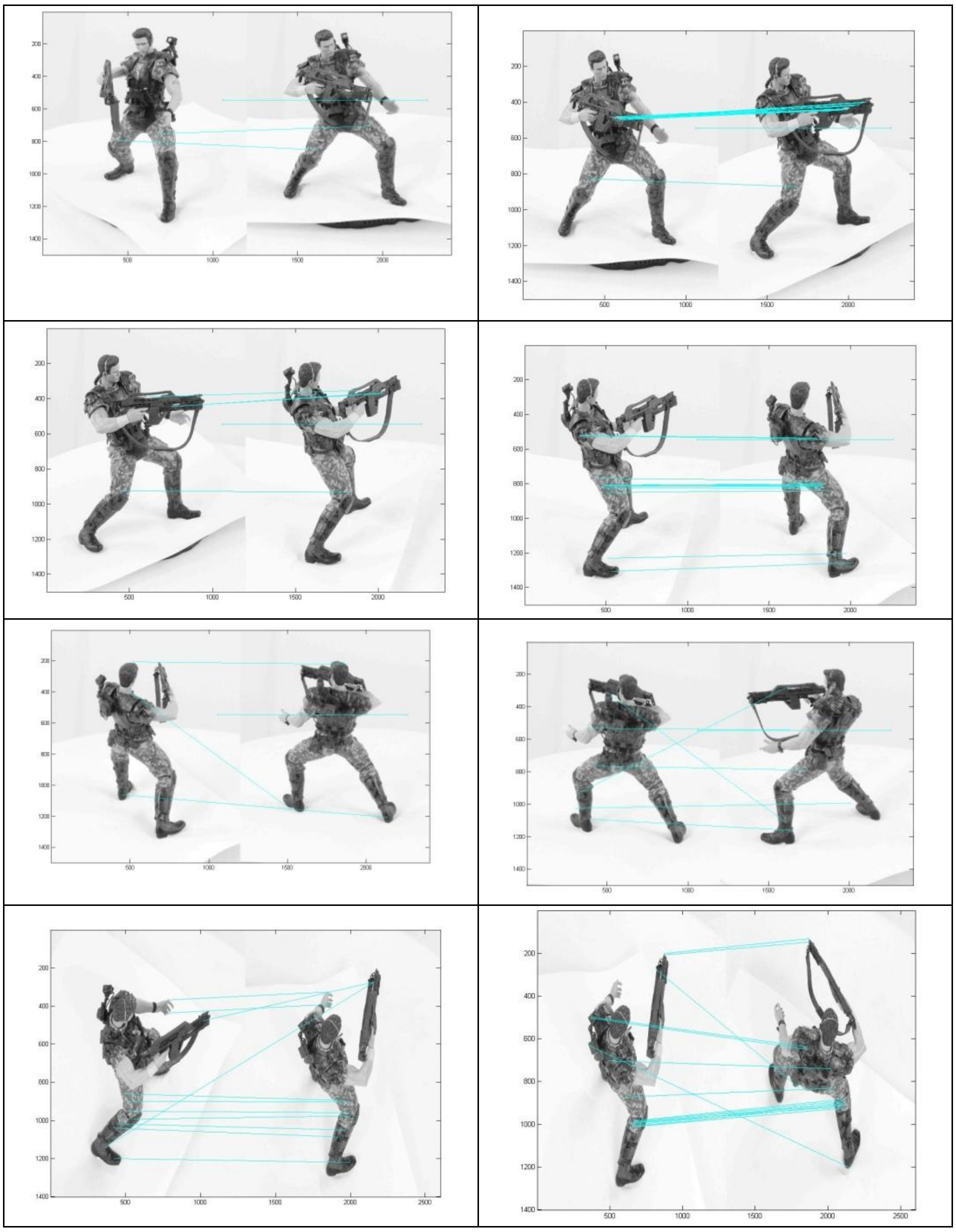


Fig 1: Resulted matching output by using the SIFT method

IV. Curvature Scale- Space Corner Detector And A Robust Corner Matching

In the used method we have used ARCSS Corner detector and a robust corner matching technique. The CSS corner detectors, in general, extract planar curves (open and close contours) from the image using the Canny edge detector and parameterize each curve using the arc-length. They then smooth the parameterized curve and calculate the absolute curvature on each point of the smoothed curve at either all scales, one, or more specific scales. Thereafter, they look for curvature maxima points as corners based on some constraints. If corners are detected at all scales, those which survive in most of the scales are selected. If corners are detected at some specific scales, they are tracked down to the finest scale to improve localization. Since the arc length of a curve is not preserved under geometric transformations like scaling, the existing CSS detectors are vulnerable to geometric attacks. The used ARCSS corner detector uses the affine-length parameterization which is relatively invariant to affine transformations. [3]

The arc-length was used to parameterize the planar curves by both the existing CSS and ECSS detectors. However, the arc-length is not invariant to affine transformations. In order to overcome this problem, the arc-length was replaced by the affine-length which is relatively invariant to affine transformations. The main difference between the arc-length and the affine-length parameterizations of planar curves is in sampling. The arc-length parameterization used by both the existing CSS and ECSS detectors selects all the points on a curve when the sample-interval is either 1 (for vertical or horizontal neighbor points) or (for diagonal neighbor points) pixels. However, as the arc-length of a curve is not invariant to geometric transformations, a substantially different set of curve points is selected from the transformed curve when the arc-length parameterization is used. In contrast, the affine-length parameterization selects only the important points of a curve. It selects more points on the curve segments where the curve makes significant direction changes (e.g., on and near corners) than on the straight-line like curve segments. Since the affine-length of a curve is relatively invariant to geometric transformations, it is expected that the affine-length parameterized curve is more stable and, therefore, leads to more stable curvature estimation than the arc-length parameterized curve. Nevertheless, while the arc-length parameterized curvature involves up to second order derivatives , the formula used by to calculate the affine-length parameterized curvature used third order derivatives. Therefore, the affine-length parameterized curvature can be exploited to extract robust corners with the same computational cost as the arc-length parameterized curvature requires, but with higher accuracy and stability.[3]

The Used ARCSS corner detector first uses the canny edge detector to extract edges (planar curves) from grayscale images. Each edge is parameterized using the affine-length and then smoothed using a medium smoothing-scale. On each smoothed curve, candidate corners are defined as the local maxima of the absolute curvature. Since the curvature of a strong corner is higher than that of a weak corner, we remove weak corners on an edge if their curvature values are lower than the predefined edge curvature-threshold. False corners are eliminated by comparing each curvature maximum with its two neighboring minima. If the curvature of a corner point is less than the double of the curvature of a neighboring minimum it is removed as a false corner. The outline of the proposed corner detector is as follows [3].

- Find edge image using the canny edge detector.
- Extract edges from the edge image: i) fill the gaps if they are within a range and select edges and ii) find T-junction sand mark them as T-corners.
- Parameterize each edge using its affine-length and smooth the parameterized curve using one of three smoothing scales determined based on the number of points on it.
- Compute absolute curvature on each smoothed curve and find the candidate corners which are the absolute curvature maxima points.
- For each edge, determine corners by comparing the curvature maxima values to the edge curvature-threshold and the neighboring minima.
- Track corners down to the lowest scale considering a small neighborhood to improve localization.
- Compare T-corners with the tracked corners and add those T-corners which are far away from the detected corners.[3]

Curvature values are lower than the predefined edge curvature-threshold. False corners are eliminated by The matching technique is Robust matching technique it is called the proposed ALTA matching technique is shown in the Image below:

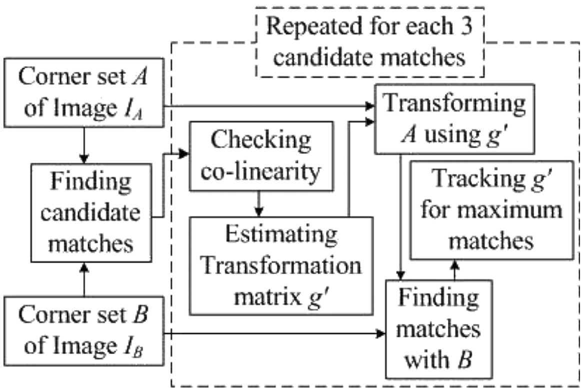
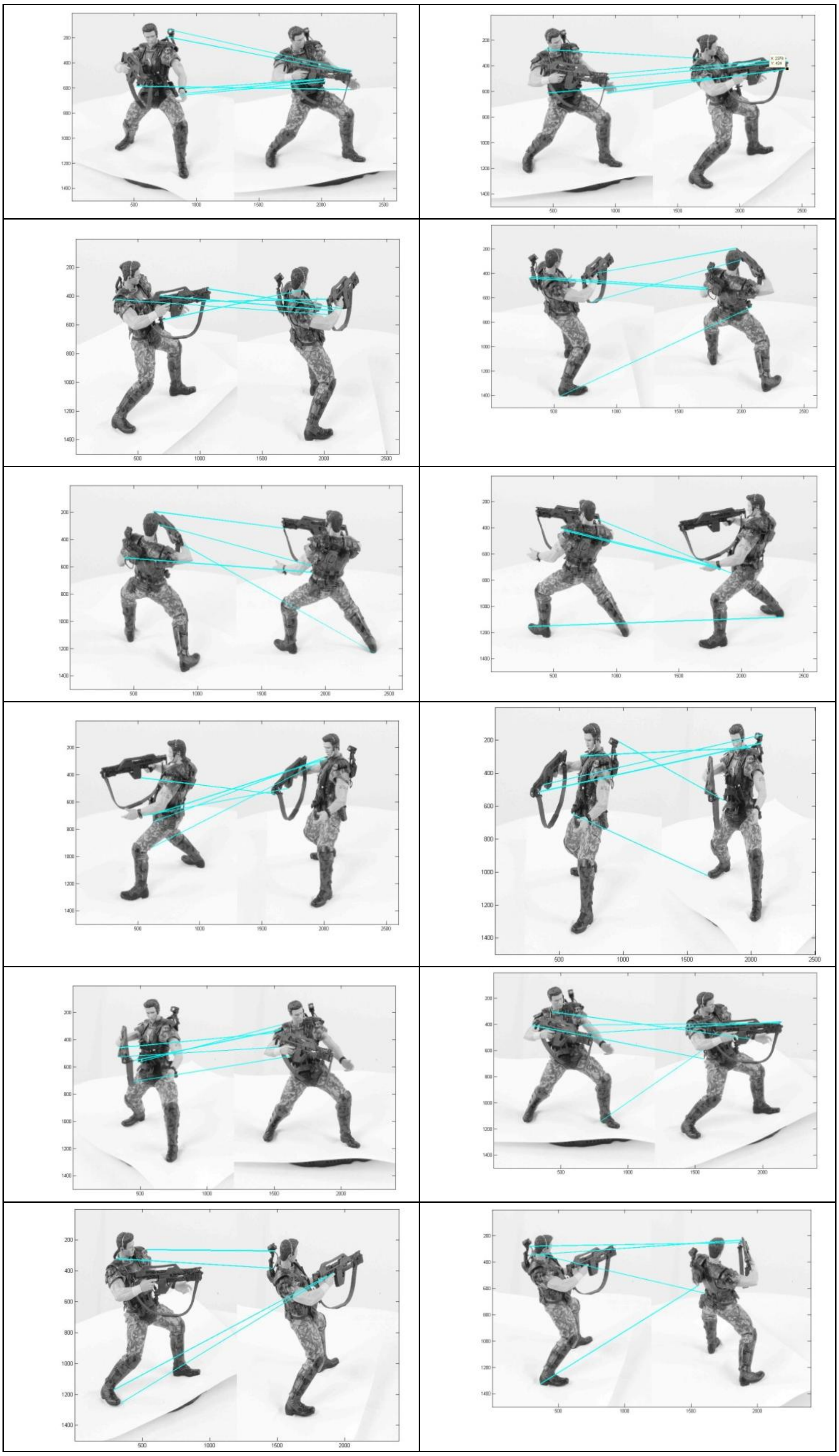


Fig. 1. Block diagram of the matching technique.[3]

For two given corner sets A and B of images I_A and I_B respectively, we first obtain candidate corner matches using curvature values and affine-lengths. For each combination of any three candidate matches, if the corners are non collinear on the respective image plane, we have two triangles—one in each image plane. If the areas of these two triangles are similar (the difference is within the certain threshold), we estimate the transformation matrix g' that transforms the triangle in I_A into the triangle in I_B . Finally, we transform the corners in A using g' and find matches within B. We keep track of g' over all iterations. The g' which gives the highest number of corner matches corresponds to the transformation matrix g we are looking for. The corner matching performance is calculated for this best matching case. Below are the resulted matching output by using this method.



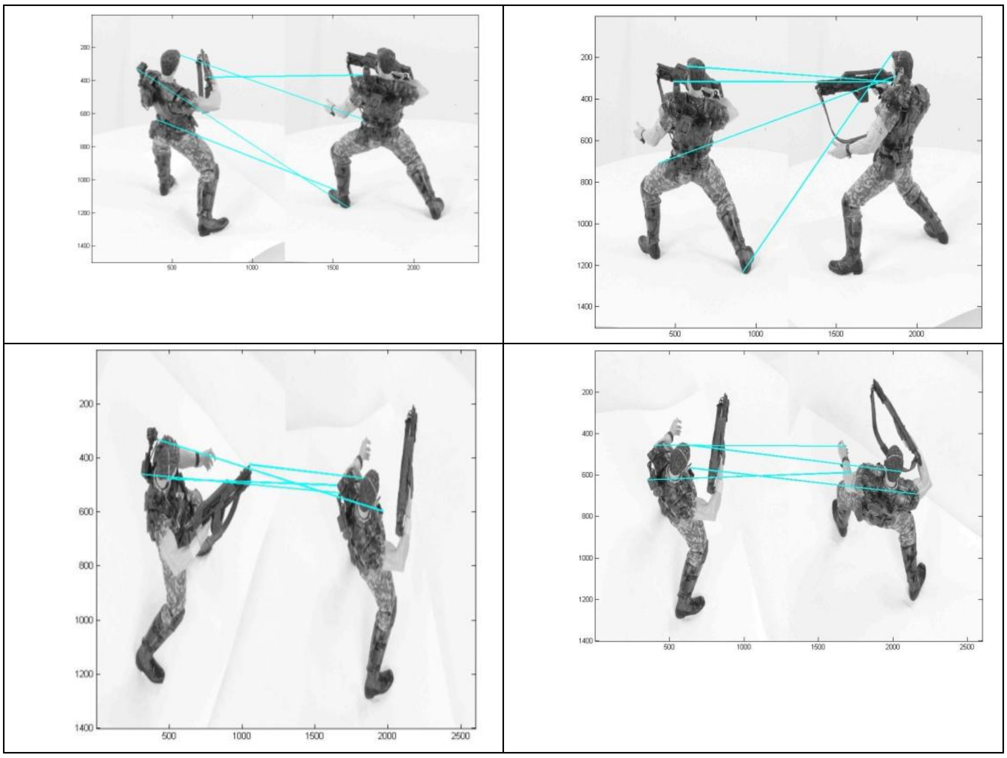


Fig 3: Resulted corner matching performance is calculated matching case

V. Comparison between the SIFT and Corner Matching Approach

The advantages of using Corners instead of key points are as follows

- Corners are visually distinguishable and more robust than their key points counterparts.
- In an image, the number of corners is much lower than the number of key points.
- Corners can be ranked based on their strength like the curvature value or the number of corners can be controlled by changing the detection thresholds. Therefore, a particular number of strong corners can be selected based on the application and it gives further reduction in computational cost during matching. In contrast, it is very hard to rank the DoG key points.
- Corner detection requires less time than key point detection in the scale-space.
- The corner–curvature combinations, though require higher matching time but perform better than the key point SIFT combinations.
- affine-length parameterized curve is more stable and, therefore, leads

VI. Conclusion

From the above discussion we can say that the Image registration is very important research area in the Image analysis and computer Vision Field. It is also one of the complex domain of the research area where a lot of work to be done for getting better results. From the Result of both our Method the we can see that in the SIFT method we get a lot of matched point but with error compared to the corner matching approach where we got less no of matched point with greater accuracy .On the other hand the second method require more time for operation then the first one. The First approach requires more storage space then the second one. So the decision for choosing of the Method to use will depend on application and available resources. In general method two shows better approach then method one.

Acknowledgements

This work is greatly supported By Dr Krishna Reddy and computer vision group of University of Trento Italy

References

[1] Barbara Zitova´, Jan Flusser "Image registration methods: a survey," Image and Vision Computing 21 (2003) 977–1000. Elsevier B.V. All rights reserved. doi:10.1016/S0262-8856(03)00137-9

[2] M. Awrangjeb and G. Lu, "Techniques for Efficient and Effective Transformed Image Identification," Journal of Visual Communication and Image Representation, 20(8), 511-520, 2009.

[3] .M. Awrangjeb and G. Lu, "An Improved Curvature Scale-Space Corner Detector and a Robust Corner Matching Approach for Transformed Image Identification," IEEE Transactions on Image Processing, 17(12), 2425–2441, 2008.

[4] M. Awrangjeb and G. Lu, "A Robust Corner Matching Technique," International Conference on Multimedia and Expo (ICME 2007), Beijing, China, 1483–1486, 2007.

[5] M. Awrangjeb, G. Lu, and M. M. Murshed, "An Affine Resilient Curvature Scale-Space Corner Detector," 32nd IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP 2007), Hawaii, USA, 1233–1236, 2007.

[6] M. Awrangjeb, G. Lu and C. S. Fraser, "A Fast Corner Detector Based on the Chord-to-Point Distance Accumulation Technique," Digital Image Computing: Techniques and Applications (DICTA 2009), 519-525, 2009, Melbourne, Australia.

[7] M. Awrangjeb and G. Lu, "Robust Image Corner Detection Based on the Chord-to-Point Distance Accumulation Technique," IEEE Transactions on Multimedia, 10(6), 1059–1072, 2008.

[8] David G. Lowe, "Distinctive image features from scale-invariant keypoints**,"** International Journal of Computer Vision, 60, 2 (2004), pp. 91-110.

[9] David G. Lowe, "Object recognition from local scale-invariant features," International Conference on Computer Vision, Corfu, Greece (September 1999), pp. 1150-1157.

[10] David G. Lowe, "Local feature view clustering for 3D object recognition," IEEE Conference on Computer Vision and Pattern Recognition, Kauai, Hawaii (December 2001), pp. 682-688.