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Homography Estimation Using RANSAC

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Abstract—**Homography is a mapping between two spaces which is often used to represent the correspondence between two images of the same scene.Homography estimation is a key step in many image processing applications such as image mosaicing, stereo vision, geo-referencing, feature matching etc as it improves stability of image registration. Homography detection using RANSAC is explained in this paper.RANSAC homography is robust and provide good set of candidate matches as it provides accurate mapping between the images..**

Keywords—**Homography, RANSAC, image mosaicing, feature based, Projective.**

I. INTRODUCTION

In computer vision and image processing the concept of feature detection refers to methods that aim at computing abstractions of image information and making local decisions at every image point whether there is an image feature of a given type at that point or not. The resulting features will be subsets of the image domain, often in the form of isolated points, continuous curves or connected regions.

Feature extraction and matching feature points is an important step in image mosaicing.Image Mosaicing is a process of assembling images of same scene into large image. The output of image mosaic is the integration of multiple images of same view into one continuous image. An image mosaic is a synthetic composition generated from a sequence of images and it can be obtained by understanding geometric relationship between images. Image mosaic is widely used in satellite and aerial photographing, meteorological and environmental monitoring, military reconnaissance and taking evidence, etc. A large number of different approaches to image mosaicing have been proposed. [1]The methods can be roughly divided into two classes:direct methods and feature based methods.The direct method estimate the transformation parameters based on the direct method estimate the transformation parameters based on the intensity difference in area of overlap. The direct method provides very accurate registration but they are not very robust against illumination variance. Feature based method is robust against illumination variance, imaging noise, image rotation, image scaling and perspective distortions. Feature based methods mosaic the images by automatically detecting and matching the features in the source images, and then warping these images together. Basically, it consists of three steps: feature extraction and matching, local and global registration and image composition. Feature extraction and matching aims to detect image features such as edges, corners and represent geometric corresponding between them..Image composite blends all images together into a final mosaic.Image mosaic tries to composite several narrow-angle images into wide-angle image.Feature matching is an important steps in image mosaic as it maps similarities between images. Homography estimation is a key process in feature matching[2]. Homography is a mapping between two spaces which often used to represent the correspondence between two images of same scene. A homography is a non-singular linear relationship betweenpoints in two images . When the world points are on a plane, their images captured by two perspective cameras are related by a 3 x 3 projective homography H. It is well known that

$$\mathbf{y = Hx}$$

where x and y are the corresponding points (homogeneous coordinates) in the first and second view respectively.Points in two images can be related by a unique homography under many other situations. It's widely useful for project where multiple images are taken from rotating camera having affixed camera centre ultimately warped together to produce a panaromic view.Homography estimation helps to improve stability of registration for feature based mosaic. There are many situations in computer vision where estimating a homography may be required such as

- Camera calibration
- 3D reconstruction
- Visual metrology
- Stereo Vision
- Scene understanding

II. Literature Survey

In the real world there exist many objects with sharpboundaries. These boundaries have been traditionally utilizedin the form of lines, points, conics and contours, to estimatevarious multi-view relationships. Conventionally higher order primitives such as lines and curves have been foundto be more robust to path compared to points. Geometriccalculations, such as estimation of homography or fundamentalmatrix, are often done robustly based on these features.Homographies have been popular in literature for variousimage and video analysis tasks. Tasks like image registrationhave been conventionally formulated as an estimationof a similarity transform relating the points in two images.These methods were primarily based on correlation usingspatial or frequency domain techniques. With the popularityof the mathematical models for imaging, homographyestimation has become an integral part of applications likemetric rectificationmosaicing and geo-referencing. The homography between two views can be computed by findingsufficient constraints to fix eight degrees of freedom, sincehomographies are defined only upto scale. Homography hasbeen estimated using many geometrical primitives.Researches on wide baseline matching[3-5],object recognition[6-7] and image/video retrieval [8] shows that feature matching is improved by spatial consistency which means the match features of each feature and its every neighbouring feature should have the same spatial arrangement.J Sivic and Andrew Zisserman[8] used each region match in the neighbourhoodof each feature match to count this feature match. The sum of counts of the whole frame decides the rank of the frame and match without count is rejected. Vittorio Ferrari [3,6] iteratively applied an expansion and contraction scheme to add new matches and remove wrong matches while expansion is fulfilled based on the similarity of affine transformations between neighbouring region matches and contraction is reached by the sidedness constraint which bases on the fact that,to a triple of region

matches, the centre of a first regionshould be on the same side of the directed line going from the centre of a second region to the centre of a third region. The median flow filter is also used to remove wrong matches, which compares the length and anger of each match vector with the median length and anger of its several neighbouring match vectors respectively and selects the one whose length and angle below the thresholds.But on the image mosaic side, there are few researches considering eliminating wrong matches before robust registration. In [9] applied the median flow filter to remove wrong matches before registration for image mosaic.For image mosaic, to locally register the neighbouring images, 8-parameter homography can be applied to accurately model the mapping between views under general image condition. RANSAC [10] is a commonly accepted way to refine thehomography between images because RANSAC can return the final inliers when getting the final homography.
Table 1 reveals different homography estimation techniques in dense manner.

Table 1 Homography estimation techniques

Technique	Primitive	Transfor-mation	Remarks
Correlation, Transform Domain Analysis	Points, Patches	Similarity	Popular for image registration. Well studied in image processing literature.
Numerically solving linear equations (DLT)	Points, Lines	Projective	Direct closed form solution. Strong dependence on accurate correspondence
Projective invariants	Conics / Polygons	Projective	Two conic correspondences; Minimal (1 pair) correspondence, approximation
Use of weak calibration	Points with additional clues	Projective	Use additional clues like Fundamental Matrix, needs correspondence for estimation.
RANSAC, ML, Least Squares Estimates	Points, Lines	Projective	Large number of possibly noisy correspondences; More robust than DLT; Very popular.
Fourier Transform of sequences	Nonpara metric Contour	Affine	Computes affine invariants and polygonal approximations of contours in Fourier domain
Fourier Transform ofimage patches	Texture	Affine	Minimal line correspondence; upto affine homographies

III.Homography Estimation using RANSAC

The RANSAC algorithm (RANdom Sample And Consensus) was first introduced by Fischler and Bolles [5] in 1981 as a method to estimate the parameters of a certain model1 starting from a set of data contaminated by large amounts of outliers in a robust manner.
The computing of the homography includes two steps. The first step is toobtain interest points and determine putative correspondences, while the second one is toestimate the homography and the correspondences which are consistent with this estimateby RANSAC algorithmThe algorithm is essentially composed of two stepsthat are repeated in an iterative fashion.

1 Hypothesize. First minimal sample sets (MSSs) are randomly selected from theinput dataset and the model parameters are computed using only the elements ofthe MSS. The cardinality of the MSS is the smallest sufficient to determine the modelparameters (as opposed to other approaches, such as least squares, where the parametersare estimated using all the data available, possibly with appropriate weights).

2. Test. In the second step RANSAC checks which elements of the entire dataset areconsistent with the model instantiated with the parameters estimated in the first step.The set of such elements is called consensus set (CS).
RANSAC terminates when the probability of finding a better ranked CS drops below a certainthreshold. In the original formulation the ranking of the CS was its cardinality (i.e. CSs thatcontain more elements are ranked better than CSs that contain fewer elements).
Given a fitting problem with parameters x , it estimates the parameters by considering following assumptions.

- •Parameters can be estimated from N data items.
- • Total M data items are available
- •Probability of a randomly selected data item being a part of a good model is Pg.
- •The probability that algorithm will exit without finding a good fit if one exists is Pfail

Now Algorithm is:
Step 1: Select N data items randomly
Step 2: Estimate the parameter x.
Step 3: Find how many data items of M fit the model. Call it as F
Step 4: If F is sufficient for processing, accept fit and exit with success
Step5: Repeat 1 to 4 M times
Step 6: Fail

If there are multiple structures then, after a successful fit, remove the fit data and repeat the steps.
M is calculated as

$$M = [\log(Pfail)] \div [\log(1 - Pg)^\wedge N]$$

Where Pfail = Probability of M consecutive failures
Pfail= (Probability that a given trial is a failure)M
Pfail=(1- Probability that a given trial is success)M
Pfail = (1-(Probability that a random data item fits the modelN)M)

Algorithm for Homography using RANSAC:
1. Randomly pick four points from each point list, A and B
2. Feed the points into homography function, and get the Resultinghomography H
3. Apply Homography to the points in point list 1 and get

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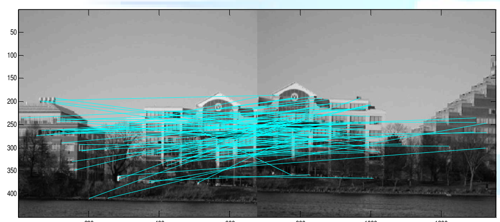
the result of putative point list.
4. Find the smallest distances between every point in the putative point list and point list2.
5. If the distances are smaller than a certain threshold defined by the user, count it as an inlier.
6. Re-do the above in a loop until it terminates.
7. The Homography that produces the most amount of inlier points will be the best Homography.

IV. Experimental Results


Image(1a) Image(1b)

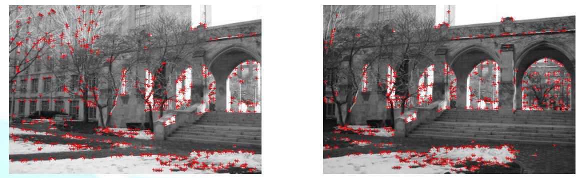
Detected corners in Image(1a) and (1b) are 138 and 114



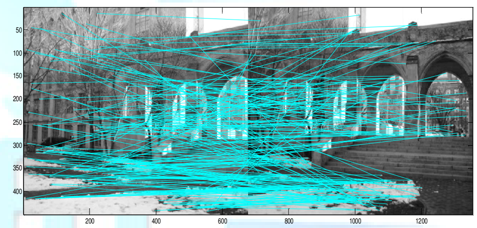
Number of matched pairs:79

Candidate matches in Image(1a) and Image(1b)

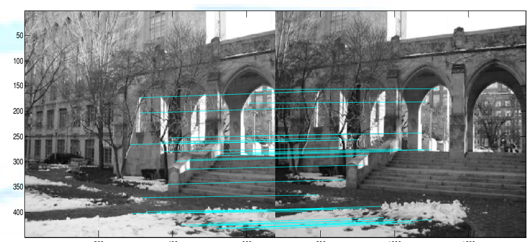

Image(2a) Image(2b)



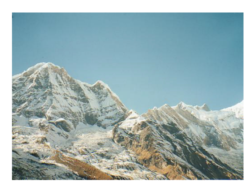
Detected corners in Image(2a) and (2b) are 229 and 189



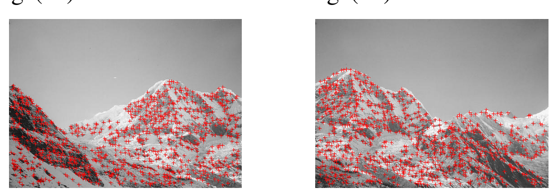
Number of matched pairs:167



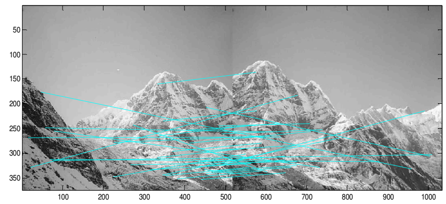
Candidate matches in Image(2a) and Image(2b)

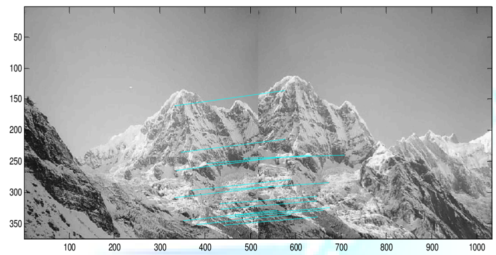
Image(3a) Image(3b)



Detected corners in Image(3a) and (3b) are 218 and 248



Number of matched pairs:64



Candidate matches in Image(3a) and Image(3b)

V. Conclusion

Homography estimation using RANSAC is a key step in feature matching as it improves the stability of image registration. It can estimate the parameters with a high degree of accuracy even when a significant number of outliers are present in the data set. On the basis of experimental results,homography estimation using RANSAC scheme is more robust than other techniques and provides accurate mapping between images and eliminates the mismatches.

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