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, Projection.

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 photography, meteorological and environmental monitoring, military reconnaissance and taking evidence, etc. A large number of different approaches to image mosaicing have been proposed. 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 step in image mosaic as it maps similarities between images. Homography estimation is a key process in feature matching. 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 between points 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

\[ y = Hx \]

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 panoramic 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 sharp boundaries. These boundaries have been traditionally utilized in the form of lines, points, conics and contours, to estimate various multi-view relationships. Conventionally higher order primitives such as lines and curves have been found to be more robust to path compared to points. Geometric calculations, such as estimation of homography or fundamental matrix, are often done robustly based on these features. Homographies have been popular in literature for various image and video analysis tasks. Tasks like image registration have been conventionally formulated as an estimation of a similarity transform relating the points in two images. These methods were primarily based on correlation using spatial or frequency domain techniques. With the popularity of the mathematical models for imaging, homography estimation has become an integral part of applications like metric rectification, mosaicing and geo-referencing. The homography between two views can be computed by finding sufficient constraints to fix eight degrees of freedom, since homographies are defined only up to scale. Homography has been 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 neighbourhood of 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 region should 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 angle of each match vector with the median length and angle 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 the homography 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

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

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 to obtain interest points and determine putative correspondences, while the second one is to estimate the homography and the correspondences which are consistent with this estimate by RANSAC algorithm. The algorithm is essentially composed of two steps that are repeated in an iterative fashion.

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

2 Test. In the second step RANSAC checks which elements of the entire dataset are consistent 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 certain threshold. In the original formulation the ranking of the CS was its cardinality (i.e. CSs that contain more elements are ranked better than CSs that contain fewer elements).

Given a fitting problem with parameters x, it estimates the parameters by considering the 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 F.
Step 4: If F is sufficient for processing, accept fit and exit with success
Step 5: 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

$$M = \log(P_{\text{fail}}) + \log(1 - P_g)^N$$

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 model)N

Algorithm for Homography using RANSAC:

1. Randomly pick four points from each point list, A and B
2. Find the points into homography function, and get the homography H
3. Apply Homography to the points in point list 1 and get
the result of putative point list.
4. Find the smallest distances between every point in the
putative point list and point list 2.
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

Detected corners in Image(1a) and (1b) are 138 and 114
Number of matched pairs: 79

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

Detected corners in Image(2a) and (2b) are 229 and 189
Number of matched pairs: 167

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

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

References


6) Vittorio Ferrari, Tinne Tuytelaars and Luc Van Gool,


