

AN ACCURATE ALGORITHM FOR AUTOMATIC STITCHING IN ONE DIMENSION

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Abstract: The paper addresses the issues in accuracy of various image-stitching algorithms used in the industry today on different types of real-time images. Our paper proposes a stitching algorithm for stitching images in one dimension. The most robust image stitching algorithms make use of feature descriptors to achieve invariance to image zoom, rotation and exposure change. The use of invariant feature descriptors in image matching and alignment makes them more accurate and reliable for a variety of images under different real-time conditions. We assess the accuracy of one such industrial tool, [AUTOSTICH], for our dataset and its underlying Scale Invariant Feature Transform (SIFT) descriptors. The tool's performance is low in certain scenarios. Our proposed automatic stitching process can be broadly divided into 3 stages: Feature Point Extraction, Points Refinement, and Image Transformation & Blending. Our approach builds on the underlying way a casual end-user captures images through cameras for panoramic image stitching. We have tested the proposed approach on a variety of images and the results show that the algorithm performs well in all scenarios.

1 INTRODUCTION

Algorithms for image stitching usually fall under two categories – one that requires manual intervention (semi-automatic) and second, fully automated stitching. Whereas the former provides high accuracy in all types of scenarios, the accuracy of the latter heavily depends upon the ability to match corresponding points between images. Image-matching methods are broadly classified in two categories: *Direct* and *Feature-based*. Feature-based methods are invariant to image scale and rotation, and are shown to provide robust matching across a substantial range of affine distortion. The first work in this area was by (Schmid and Mohr, 1997). Lowe extended the approach to incorporate scale invariance (Lowe, 2004). In comparative research presented by (Mikolajczk and Schmid, 2003), the SIFT method has shown superiority over classical methods for interest point detection and matching. In most of the tests, Gradient Location Orientation Histogram (GLOH) obtained the best results, closely followed by SIFT.

In our approach we iteratively used K-d trees (Friedman et al., 1977) matching algorithm to

choose the best matches in the image pair. We then used a match refinement approach, which uses the slopes of the imaginary lines formed by joining the corresponding feature points, if the two images are stacked horizontally. Further, RANSAC (Fischler and Bolles, 1981) was used to reject many false matching points. The Probabilistic model (Matthew Alun Brown, 2000; Lowe, 2004) is used for image-match verification to distinguish correct image match and incorrect image match based on the set of inliers/outliers generated by RANSAC. The sufficient and well-distributed matching points selected through adaptive non-maximal suppression (ANMS) are used for image transformation. Projective transformation is suitable for our cases, and gives better image-aligning results compared to other transformation methods for chosen matching points.

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2 PROBLEMS DURING IMAGE STITCHING

We found the occurrence of many false matching pairs in image matching. When used for image registration, this produced undesirable results. Further duplicate matches in one image result in wrong transformation for the image. We tried stitching our dataset images, shot under a variety of conditions, using the demo version of AutoStitch. AutoStitch failed to stitch images in some cases. Information loss, such as number plate of the vehicle happens during stitching. Such information might be needed further. Alignment in a few results is incorrect even in the presence of perfectly matching points found through SIFT features.

3 OUR 3-STAGE APPROACH

The following flowchart shows the overview of our proposed approach.

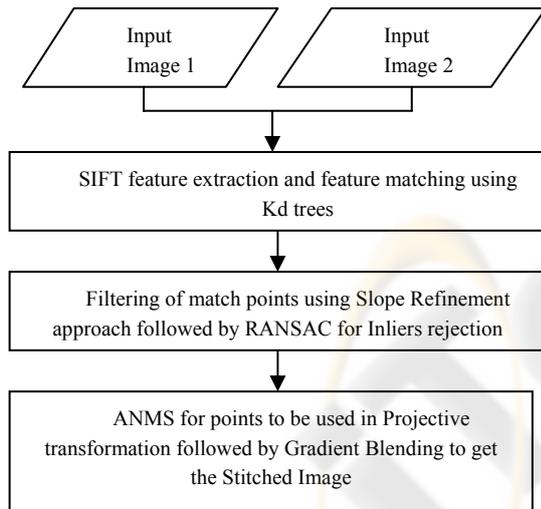


Figure 1: Flow Chart of Our proposed three-stage Automatic Stitching Process.

3.1 SIFT Features Matching

We extract the SIFT features from all the images and use them for image matching and alignment (Lowe, 2004). In order to choose strong keypoints, we consider the extrema in the local neighbourhood by a threshold, which is determined as follows:

$$\text{Threshold} = 0.04 / S \quad (1)$$

where S is the number of scales in each octave of the Difference of Gaussian Scale Space. We

iteratively change this value and obtain a sufficient number of matching key points.

3.2 Refinement of Match-Points Using Slope Orientation

The basis of this step lies in the way people shoot panoramic images. It is rare for people to twist the camera relative to the horizon. We analysed the dataset extensively and found a high degree of consistency regarding the shooting patterns. The matches we arrived at after the feature-points-matching stage still had false and/or duplicate matches. We chose to refine these matches in order to reject the false matches by exploiting the above-mentioned heuristic.

The refinement approach was used to find the primary match that would always be a correct match of points between two images, and to find all other matches, which agree with the primary match.

After we get 20 strongest matches from the previous step, we plot these points on the two images stacked horizontally, and draw imaginary lines connecting the corresponding points.

For each match – X_{mi} corresponds to X_{nj} , where i th feature in X_m image matches with j th feature in X_n image, we calculated the slope of the imaginary line formed by connecting the corresponding points. Using all these slopes, we found the slope, M , such that the sum of deviation of all the slopes from M is minimum. Through extensive analysis on our dataset, we found that this slope M always corresponds to the correct matching points between the images. We identified all other matching points whose slopes were within a threshold of the slope M . RANSAC has been added to filter false matching points based on geometric property using the RANSAC algorithm (Fischler and Bolles, 1981) It has the advantage of being largely insensitive to outliers, but fails if the outliers are more than 70-75%.

3.3 Image Transformation

3.3.1 Adaptive Non-Maximal Suppression (ANMS)

After getting correct matching points, the required number of matching points for image transformation is to be selected. Because for image-stitching applications the area of overlap between a pair of images is small (about 20% to 30%), the selected matching points for image transformation should be spatially well distributed over the image. This can be

done using ANMS to select a fixed number of interest points from each image (Carneiro and Jepson, 2003). Based on a maximum in the neighbourhood of the radius r , desired number of pixels are retained. Conceptually, we initialise the radius to zero and then increase it gradually till the desired number of interest points is obtained. These points are obtained by taking one matching point and suppressing other matching points within the updated radius.

3.3.2 Projective Transformation

Affine transformation maps any coordinate system in a plane to another coordinate system that can be found from above projection. Under affine transformation, parallel lines remain parallel and straight lines remain straight. When we look at an object at a finite distance in a plane from an arbitrary direction, we get an additional "keystone" distortion in the image. This is a projective transform, which keeps straight lines straight but does not preserve the angle between lines. This warping cannot be described by a linear affine transformation. Therefore, we have used projective transformation for image aligning.

3.3.3 Gradient Blending Method

In the overlapped area, the image-blending algorithm calculates the contribution of the new image and the composite image at every pixel. A look-up table is created for each new image. This table contains the size and shape of the overlapped area. This look-up table is normalized to define what proportion of intensities of two overlapped regions is used for generating the new composite image. One value of the normalized look-up table can be perceived as a weighing factor (α) at every pixel, which is calculated as the distance from the image edge as shown in the equation (2).

$$N(x, y) = \alpha * I(x, y) + (1 - \alpha) * C(x, y) \quad (2)$$

where $C(x, y)$ is the composite image pixel (before placing the new image), $I(x, y)$ is the new image pixel, and $N(x, y)$ is the new composite image pixel (with new image added).

4 RESULTS AND ANALYSIS



Figure 2: (a) Left Image.

Figure 2: (b) Right Image.



Figure 2: (c) Our Method Matching Points.

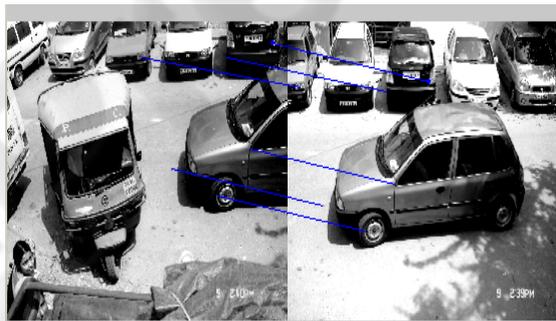


Figure 2: (d) Selected Matching through ANMS for image transformation.



Figure 2: (e) Stitching Result by our method.



Figure 2: (f) AutoStitch Result.

Figure 2 (f) shows the result of stitching of input images, which are shown in figures 2 (a) & 2(b), using AutoStitch. It shows the misalignment of the input images at overlapping car portions of the stitched image, which is shown in the figure 2 (f). The result of our method is shown in the figure 2 (e), which is perfectly aligned. We also observed that there is a loss of information in another set of image during image stitching for vehicle number plate. Our results are robust for these types of losses due to perfect alignment using good refinement methods to select correct matching points for the image transformation. We can also observe misalignment in AutoStitch image-stitching results. This misalignment is addressed properly in our approach results.

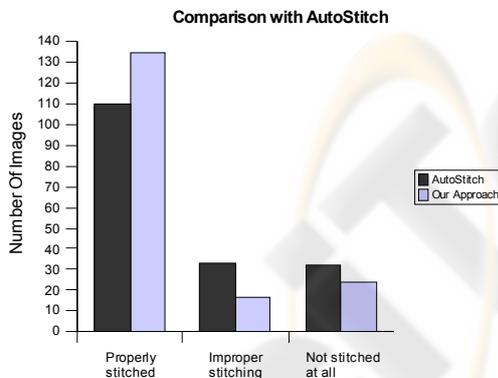


Figure 3: Comparison of our approach versus AutoStitch.

5 CONCLUSION & FUTURE SCOPE

We could stitch the images perfectly where AutoStitch gives incorrect results such as wrong alignment of images or loss of information during image stitching. Also we could stitch images had a small difference in the Depth Of Field view and

which could not be stitched by AutoStitch. We restricted ourselves to 1-D panoramic stitching problem, though our approach can be extended to 2-D stitching as future work.

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