COMPARING DIFFERENT PANAROMIC IMAGE STITCHING ALGORITHMS

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ABSTRACT

Image stitching is one of the most successful applications in Computer Vision. Nowadays, it is hard to find a mobile phone or an image processing API that does not contain this functionality. The idea of our project is to create various panorama image stitching systems that combine multiple photographic images with overlapping fields of view to produce a segmented panorama or high-resolution image, and compare their performances. The process involves Feature Extraction through keypoint detection in images, followed by determining local invariant descriptors in images using these 4 methods separately- SIFT, SURF, ORB and BRISK. After feature extraction, we match corresponding features between images using BruteForce Matcher and KNN technique. Homography estimation using RANSAC is performed that returns a 3x3 matrix of transformation which is a combination of scale, rotation, shear and translation methods. The final step involves applying the obtained homography transforms to one image, warping its perspective to match the other image, and then histogram equalization resulting in the final panorama image.

Index Terms— SIFT, SURF, ORB, RANSAC, Homography

1. INTRODUCTION

A panoramic image is the image which is a combination of multiple sets of images and joined together to give a wider view of a scenario compared to a single image. Using multiple image stitching techniques we can create high resolution panorama images by combining images taken from different perspectives. This is one of the most popular applications in the modern era of image registration and blending of images for the formation of wide angle images. With the increase in sizes of images, the speed of the feature extraction and matching play a vital role in deciding which algorithm should be used. In this project we compare various traditional as well as modern feature extraction algorithms on the basis of their speeds. The results from matching and extraction are used for finding homography matrices for estimating homography which uses the RANSAC algorithm to iteratively remove unwanted inliers. The output from the above algorithm is used for blending the two images, followed by some post-processing steps to obtain the panorama.

2. LITERATURE REVIEW

1. “SURF applied in Panorama Image Stitching” by Luo Juan and Oubong Gwun, image stitching is performed by using a modified SURF algorithm. Combining this with image blending and matching algorithms, the final results were obtained. Firstly, descriptors were found using modified SURF followed by finding and matching pairs. Secondly, performing K-NN checks thereby reducing the bundles using RANSAC. This was finally blended with the other images. Comparing these results with the traditional SIFT based approach, was the basis of the paper.

2. “Distinctive Image Features from Scale-Invariant Keypoints” by David G. Lowe, presents a fast and reliable method which is both invariant to scale and rotation for matching of different views of an image. This method provides robustness across a wide range of affine distortion.This paper also talks about an approach to use the above features in object recognition, followed by matching these features to another data set using a fast paced k-NN approach. Following which Hough transform is performed to identify clusters of the same object.

3. “Image Mosaic Based on Sift” by Yang zhan-long and Guo bao-long, automatic mosaic technique based on SIFT was proposed. Here key points are extracted over every scale and positions in the image, followed by defining descriptors according to the key points obtained. This was followed by removing less relevant features by applying RANSAC. Finally, calculating the homography for transformation and obtaining the final stitched image

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3. METHODOLOGY

The panoramic image stitching incorporates the following steps of action- Feature extraction and key point detection: The initial step of image stitching involves feature extraction and keypoint detection in the images. This is done by using some robust corner detection algorithms which are both rotation and scale invariant. For obtaining feature descriptors, we have experimented with 4 completely different feature description algorithms and compared their relative performances qualitatively and quantitatively.

Feature Extraction:

1. **ORB (Oriented FAST and Rotated BRIEF)-**

   ORB is a fusion of FAST keypoint detector and BRIEF descriptor with modifications to enhance the performance. ORB uses FAST for keypoint detection and then applies Harris corner measure to find top N points among them. It determines the intensity-weighted centroid of the patch with the corner located at center. The direction of the vector from this corner point to the centroid is used for calculating orientation. ORB is much faster than SURF and SIFT and ORB descriptor works better than SURF for most practical uses.

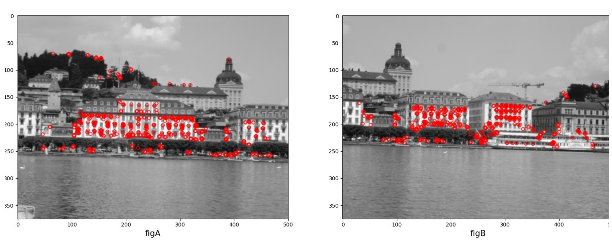

Fig. 1. Feature Extraction using ORB

2. **BRISK (Binary Robust Invariant Scale Keypoints)-**

   BRISK descriptor is based on a hand-crafted sampling pattern which sets it apart from other descriptors like BRIEF and ORB and is also invariant to rotation.It is equipped with a mechanism for orientation compensation which involves estimating the orientation of the keypoint. Descriptor building is done by performing intensity comparisons. BRISK outperforms ORB in photometric changes – blur, illumination changes and JPEG compression.

3. **SIFT (Scale-Invariant Feature Transform)-**

   SIFT keypoints of objects are first extracted from a set of reference images which are stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to the existing database and then based on Euclidean distances of feature vectors finding candidate matching features. The subgroups of keypoints that are in agreement with the object and its location, scale, and orientation in the new image are identified to filter out good matches from the full group of matches. It uses an efficient hash table implementation of the generalised Hough transform to rapidly determine the consistent clusters.

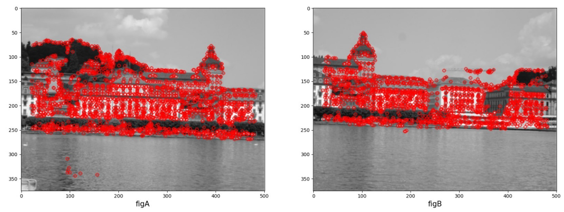

Fig. 2. Feature Extraction using Brisk

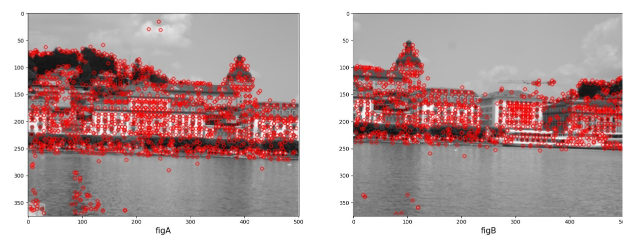

Fig. 3. Feature Extraction using SIFT

4. **SURF (Speeded-Up Robust Features)-**

   SURF is a speeded-up version of SIFT. SURF approximates Laplacian of Gaussian (LoG) with Box Filter, unlike SIFT that uses Difference of Gaussian. One big advantage of this approximation is that convolution with a box filter can be easily calculated with the help of integral images. Also, SURF relies on the determinant of "Hessian" matrix for both scale and location. SURF uses Wavelet responses in horizontal and vertical direction for feature description

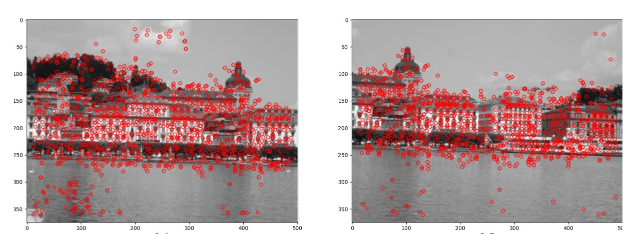

Fig. 4. Feature Extraction using SURF

Feature Matching:

In the second step, we need to identify pairs of features which are highly similar to one another in both the images that can help us deduce the transformation matrix in the next steps. We have used the following approaches for the feature matching:

1. **Brute Force:** In this approach we match the closest features in both the feature arrays. This returns a single set of closest i-th and j-th independent pairs. With cross-checkings set as True, it would only select a single set of closest neighbours which would be used for further processing.

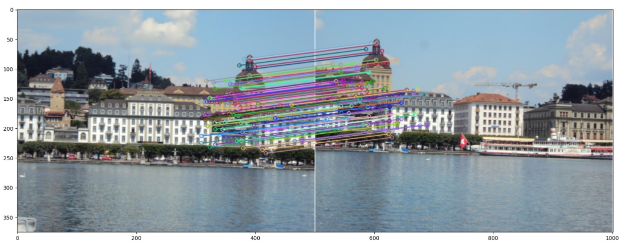

Fig. 5. Feature Matching using SURF-Brute Force

2. **K-Nearest Neighbours:** In the following approach, we match two features based solely on the distance between them. We also need to invalidate cross-checking which would allow any given feature to form multiple such pairs using a specific threshold. By using the Lowe's Ratio Test, we ensure that both the neighbours are close enough to be called as similar

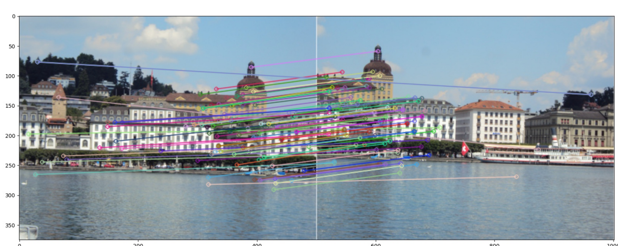

Fig. 6. Feature Matching using SURF-K-NN

Homography Estimation:
We need to compute the transformation matrix that will stitch the 2 images together based on their matching points. Such a transformation is called the Homography matrix, which is a 3x3 matrix that can be used in many applications such as camera pose estimation, perspective correction, and image stitching. In conjunction with this we have used RANSAC (RANdom SAmple Consensus) which is an iterative algorithm to fit linear models and is robust to outliers. Models like Linear Regression use least-squares estimation to fit the best model to the data. However, ordinary least squares is very sensitive to outliers. RANSAC solves this problem by estimating parameters only using a subset of inliers in the data.

Warping Perspective:
Once we have the estimated Homography, we need to warp one of the images to a common plane. We have applied a perspective transformation that combines rotation, scale, translation or shear. The idea is to transform one of the images so that both images merge as one. To do this, we can use the OpenCV'ss warpPerspective() function that takes an image and the homography as input. Then, it warps the source image to the destination based on the homography.

Post processing:
To obtain the final panorama image, we use cropping and thresholding to merge the 2 images. Histogram equalization is also applied which usually increases the global contrast of provided images.

4. EXPERIMENTS

Here is a detailed example of three images to be stitched together and the aforementioned methodology applied on it step by step:

Fig. 7. First image

Fig. 8. Second image

5. RESULTS

We applied Feature Extraction, Feature Mapping, Homography Estimation and Image Warping to give us an panorama image for images 1 and 2. We repeated the same steps for the output image of images 1 and 2, to image 3 that gives us the final panorama image for all three images combined.

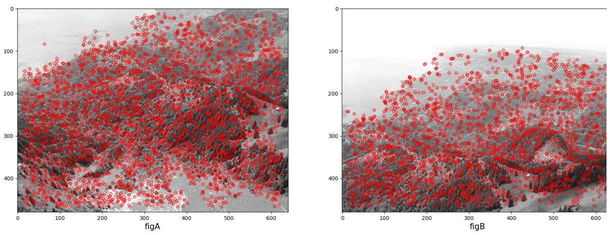

Fig. 9. Feature extraction using SURF

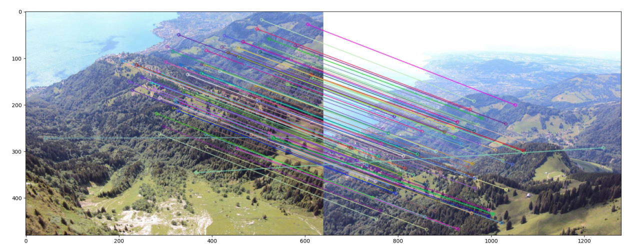

Fig. 10. Matches for two images combined

Fig. 11. Two images combined

Fig. 12. third image

6. CONCLUSION

By experimenting our implementation on numerous images, we found that ORB combined with Brute force- feature

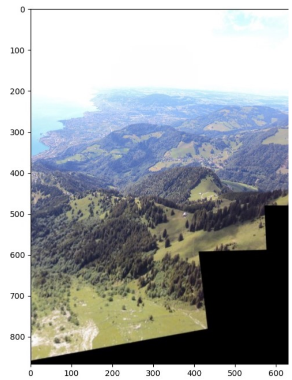

Fig. 13. Final result obtained

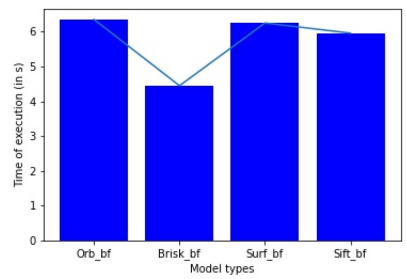

Fig. 14. Bar graph for Brute force methods

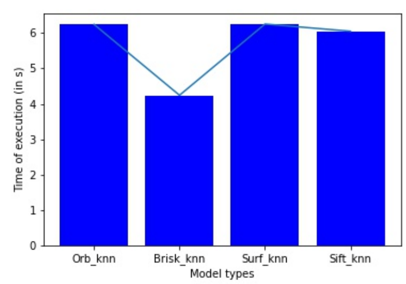

Fig. 15. Bar graph for K-NN methods

matching results in the best speed-wise performance. However, SURF combined with K-NN produces the least outliers and best matching qualitatively.

7. REFERENCES

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Algorithm	K-NN	BF
Orb	4.2419	4.448
Brisk	6.049	5.957
Sift	6.253	6.250
Surf	6.242	6.351

Table 1. Time taken for full implementation by each algorithm

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