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RESEARCH ARTICLE

Performance Analysis of Feature based Multiple Descriptors with Histogram Equalization for Image Mosaicing

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Abstract

Objectives: The main objective of the proposed work is to develop an image mosaicing model for combining the images of different individual images. In other way, the union of two images and to evaluate the performance of the model in terms of the number of run time in seconds and number of key features they use. **Methods:** In this work, the Histogram Equalization is a processing step required to make the mosaic invariant to intra image and inter image intensity variability. The detailed feature of the enhanced image is extracted using Scale-invariant feature transform (SIFT), Oriented Fast and Rotated Brief (ORB), Binary Robust invariant scalable key points (BRISK) feature descriptors techniques. The features including local and global are matched using K-Nearest Neighbor. Then, homography is performed using RANdom SAmple Consensus (RANSAC) algorithm to compute the camera motion. Finally, the image warping is performed using smoothing filter of size 40x40 to obtain the panorama image. **Findings:** The model is tested on various datasets using three different feature extractors popularly used in image mosaicing or image stitching algorithms SIFT, ORB and BRISK descriptors. It is observed that the ORB is the best feature extractor among the state-of-the-art feature extractors. The ORB with HE uses a minimum of 500 key features to match the images and generates panoramic images that are invariant to shift and rotation with the minimum run time of 0.0836 seconds. **Novelty:** The state-of-the-art models developed by the researchers suffer with good number of matching points of the input images to generate the image mosaicing. This issue is addressed in the proposed model using multiple descriptors SIFT, ORB and BRISK techniques. The ORB with HE will provide the minimum key features and enough good matches of features with the record of minimum runtime to obtain the panoramic images.

Keywords: Mosaicing; Smoothing Filter; Histogram Equalization; Homography; Panorama Images

1 Introduction

Image mosaicing is nothing but the combination of multiple photographic images which are captured with different fields of views to generate a segmented panorama of images having high-resolution pattern. It is performed using computer software and requires nearly exact overlaps between images and identical exposures[1]. The images must be planar homography only in case of scene reconstruction for mosaicing. It is generated from a sequence of images and provides better understanding of geometric relationships between images. These geometric relations relate the different image coordinate system. It is possible to reconstruct a single image which is more distinct compared with a single large image of the same object, which covered the entire visible area of the scene by applying appropriate transformations through a warping and merging operations[2]. The warping and merged image operations results in generations of mosaicing image. The process of mosaicing will be performed in direct and feature based method. In the case of direct model, the registration process is accurate, but it suffers from very robust against illumination variance. Whereas in the case of feature-based models, it is more robust against illumination variance, image noise, image rotation, image scaling and perspective distortions. Figure 1 shows the main steps to be performed in image mosaicing are feature extraction, image registration, stitching and blending[3].

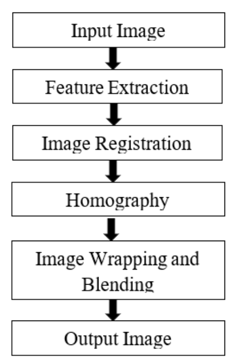

Fig 1. Basic steps of Image Mosaicing

The images are captured to act as an input image. The features of the images are extracted in view of corner or edges of the images[4]. Once the features are extracted, then the process of image registration is performed and seems to be a very important factor in the field of image processing. The operation of image registration is performed to obtain the final information that is received from the combination of sources like in image mosaicing, image fusion and image restoration. It is the process of aligning two or more images taken from one point or the same thing is captured from different points. The moment to perform registration is to create geometric correspondence between images. The goal of registration is to establish geometric correspondence between the images so that they may be transformed, compared, and analyzed in a common reference frame. After registration, then homography is performed, in this process undesired corners which do not belong to the overlapping area are removed[5]. The Random Sample Consensus (RANSAC) algorithm is used to remove the undesired corners in the image. It plays a vital role in image processing applications that includes as image mosaicing, feature matching as it improves the stability of image registration and provides a good set of image samples matches as it provides accurate mapping and removes the false sample matches in the image pairs[6]. The process of reprojections of frames are carried out with the proper size, length, width. The Stitching using wrapping and blending is done to obtain a final output mosaic image[7]. Addressed the image stitch mechanism using Grid-based motion statistic (GSM) image feature matching algorithm. The ORB is used to detect/describe the feature points. Bilateral matching is used to find out matched sets. The RANSAC is used to obtain the basic matrix of the image features. The homography matrix is selected between the two images[8]. To fuse the aligned image, the weighted fusion algorithm is adopted. Once the fusion operation was carried out then the color and brightness nature of the reconstructed images seams better and seems to be natural and real.[5] considered the two images to find out the overlapping regions. Here, detection of overlapping regions and the common pixels point are matched between the two images. The bidirectional scanning is performed to determine the overlapping region between the two regions. After detection, alpha blending is used to reduce the breakages from the retrieved image.[9] developed the document stitching (optimal). The overlapping region and optimal seam are detected. The edges of the images are detected using Sobel operator and Hough transform to find the line segment. The feature points were detected using SURF model. The Ostu's algorithm is adopted to search for optimal seam.[10] extracted the features of the image. The characters are being recognized using an intelligent algorithm. The reconstruction process of the shredded document is based on the text and document processing.[11] developed the model based on the feature technique for mosaicing of color image of the human retinal. The mSIFT technique detects the significant features of color images. The interesting point of the extracted features of the two images are detecting by Euclidean distance. The panoramic images are obtained using pairs of images.[12] adopted a model for extraction of features using the Y-position method across the image. The PCA is used to find out the initial Y position. The quality of mosaic image depends on the selected reference frame. The short path from all other references frames simply reduced registrations to obtained mosaic image.[13] addressed mosaicing process with SURF technique for Image Warping/blending techniques. The SURF technique is used to detect the features of the input images. Next, the directed line segments are described and then the points are matched. Once the geometrical alignment was completed then warping/blending operations are to be performed.[14] used the FAST detector to extract the features of the images. The experiment shows FAST corner detector and FREAK binary descriptor better in case of real time applications. The Intel Compute Stick and Lenovo Idea center Stick hardware devices are used for the real-time image mosaicing.[15] used SIFT based algorithm to generate panoramic image. The SIFT is used to extract feature points, then the descriptors defined on the key point neighborhood are computed. The homography calculation was carried out using RANSAC algorithm and produces the image mosaic generating panoramic image.[16] explained the improved SIFT algorithm, evaluated with an open-source algorithm using structural similarity index measure and mosaicing computational times for mosaic accuracy and processing efficiency, respectively.[17] SWM based Color Image Mosaicing and DCT based CIM on FPGA is addressed in this paper. These models are used for corner detection of two images and perform the automatic image registration whereas DCT based CIM aligns local and global alignment of images using phase correlation method.[18] addressed feature-based corner detection for mosaicing images. Here the feature techniques extract accurate corner positions and offer a high degree of pipelining and parallelism and hence produces high throughputs and offers better reconstructed image quality[19]. The rest of the paper is organized as follows; Section 2 addressed the proposed model. The implementation of the model is discussed in section 3. The results and their analysis will be carried out in section 4. The conclusion and the scope of the proposed work is done in section 5.

2 Methodology

In the proposed model, the left and right images of an individual scene are considered as an input. The right image is histogram equalized to the left image. Next, the significant feature of the enhanced image is extracted using Scale-invariant feature transform (SIFT), Oriented Fast and Rotated Brief (ORB) and Binary Robust invariant scalable keypoints (BRISK) feature descriptors techniques.

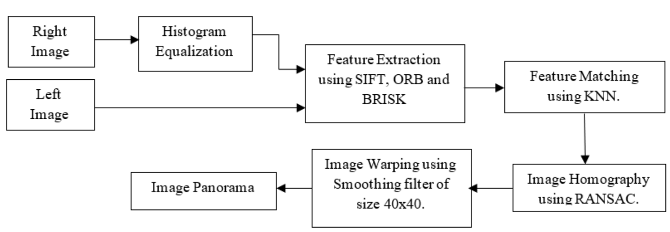

Fig 2. Proposed Image mosaicing model

Later, the local and global features of the model are matched using K-Nearest Neighbor (KNN) technique. In the field of image mosaicing, any two images (assumed to be in the same planer surface) are related by the homography (pinhole camera model).

The homographies helps to compute the camera motion (rotation and translation between the two images). The RANSAC is applied on the images to compensate for a large proportion of outliers in the data. The image warping operation is performed using Smoothing filter having the filter size of 40x40 to obtain the mosaic image. The proposed image mosaicing model is shown in Figure 2.

2.1 Image Dataset

The image samples of three datasets are used for experimentation of proposed model. Two images such as image 1 and image 2 are used for dataset 1 (mountain) and 2 (foot) respectively. The sample images of three datasets having the size of 128x128 are shown in Figures 3 and 4.

Image 1 Image 2

Fig 3. Image Dataset 1

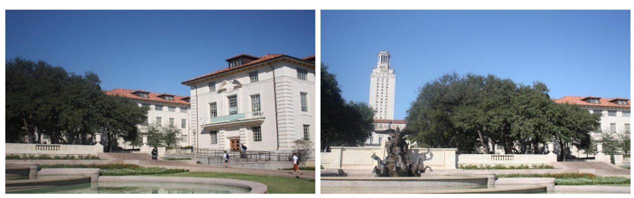

Image 1 Image 2

Fig 4. Image Dataset 2

Scale-invariant feature transform: To achieve scale invariance, SIFT constructs an image pyramid by building multiple layers of the input image, with each layer down sampled and convolved with Gaussian filters of increasing sigma values. This process creates a scale space representation of the image. The Difference of Gaussian (DoG) is computed by taking the difference between adjacent layers in the pyramid, which helps identify scale-space extrema or potential key points. SIFT addresses rotation invariance by assigning key point orientations based on the local image gradient. The algorithm computes the gradient magnitude and orientation around each key point and assigns the dominant orientation(s) to the key point. This enables the key points to be robust to rotations. SIFT also considers affine transformations, changes in intensity, and viewpoint changes. By constructing descriptors based on the local image gradient magnitudes and orientations, SIFT captures the distinctive characteristics of key points. These descriptors are designed to be invariant to affine transformations, changes in intensity, and certain viewpoint changes, allowing for accurate matching and recognition.

Oriented FAST and Rotated BRIEF: The ORB algorithm is a feature detection and description method used in computer vision and image processing. It combines the FAST key point detector and the BRIEF descriptor with some modifications. The ORB algorithm starts by using the FAST (Features from Accelerated Segment Test) detector to determine the key points in an image. FAST is a corner detection algorithm that identifies corners based on the intensity differences between pixels. However, FAST does not compute the orientation of the detected corners and is rotation variant. To address the rotation variance, ORB applies the Harris corner measure to the FAST key points and selects the top N points based on their response. The Harris corner measure helps identify the most significant corners in terms of local image structure. Next, ORB computes the orientation of each selected key point. It calculates the intensity-weighted centroid of the patch with the located corner at the center. The direction of the vector from the corner point to the centroid gives the orientation. Additionally, moments are computed to further improve rotation invariance. Once the orientations are determined, ORB computes a rotation matrix for each key point using its orientation.

Binary Robust Invariant Scalable Key points: The BRISK descriptor utilizes a predefined sampling pattern that samples pixel over concentric rings. This sampling pattern helps to capture information at different scales and orientations around a key point. In the BRISK algorithm, for each sampling point in the predefined pattern, a small patch is considered around it. Prior to performing any computations, this patch is smoothed using Gaussian smoothing. The purpose of the Gaussian smoothing is to reduce noise and make the descriptor more robust to small variations in the image. By applying the predefined sampling pattern and smoothing the patches using Gaussian smoothing, BRISK aims to create a descriptor that is invariant to changes in scale and rotation. BRIEF uses a binary descriptor and does not employ a specific sampling pattern, while ORB uses a combination of the FAST key point detector and the BRIEF descriptor with additional modifications for rotation invariance.

2.2 Panorama Images without Histogram Equalization

The panorama images obtained on the three datasets without Histogram equalization are shown in Figures 5 and 6. The multiple descriptors are directly applied on the datasets to warp images. In absence of Histogram Equalization, when the images are warped, there may be more existence of seams in between the two input images.

Fig 5. SIFT, ORB and Brisk descriptors panorama images without Histogram Equalization for Image Dataset 1

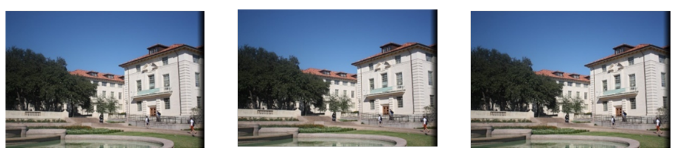

Fig 6. SIFT, ORB and Brisk descriptors panorama images without Histogram Equalization for Image Dataset 2

2.3 Panorama Images with Histogram Equalization

Histogram Equalization is used for contrast adjustment using the image 's histogram. It increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Using histogram equalization module to remove any intensity variation between the scenes is necessary. Though we see that the results have overhead of time it is still a good pre-processing step when dealing with mosaicing of images taken from satellites, microscopes etc., where the intensities have vast inter-image and intra-image variabilities. The panorama images obtained on the three datasets with the presence of Histogram equalization are shown in Figures 7 and 8.

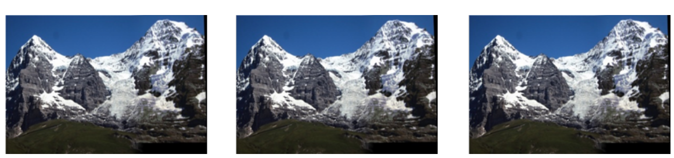

Fig 7. SIFT, ORB and Brisk descriptors panorama images with Histogram Equalization for Image Dataset 1

2.4 Feature Matching using KNN

However, for the cases for more than one candidate match, then KNN based matching procedure is more successful to apply for the proposed model. The value of 'K' is pre-defined by the user. The KNN also provides a larger set of candidate features

Fig 8. SIFT, ORB and Brisk descriptors panorama images with Histogram Equalization for Image Dataset 2

and these matching pairs are robust in their matching procedure. The matching images using KNN for multiple descriptors on three datasets are shown in Figures 9 and 10.

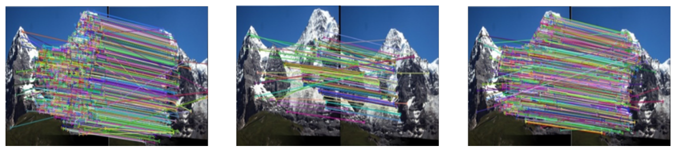

Fig 9. Matching of SIFT, ORB and Brisk descriptors panorama images for Image Dataset 1

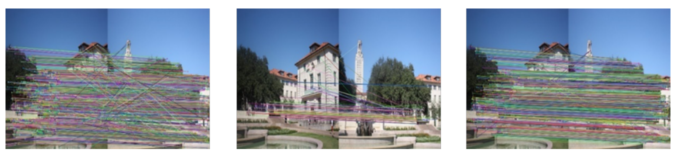

Fig 10. Matching of SIFT, ORB and Brisk descriptors panorama images for Image Dataset 2

2.5 Image Homography using RANSAC

Homography calculation is the next step for image registration where the undesired corners which do not belong to overlapping area were removed. For homography, the RANdom Sample Consensus (RANSAC) algorithm is used for fitting models in the presence of available data outliners.

Let the two sets of points L1= {a1, a2,…aN} and L2={a’1, a’2,….a’N} then the Image homography is performed by using RANdom Sample Consensus (RANSAC) algorithm.

- Step 1: Randonly pick four points from each set L1 and L2.
- Step 2: Feed the points into homography to obtain H.
- Step 3: Apply homography to obtain the result of putative point set.
- Step 4: Find the minimum distance between every point in putative set 1 and point set 2.
- Step 5: If the distances are smaller than threshold, count the inlier.
- Step 6: Repeat step 1 to 5, till it terminates.
- Step 7: The homography that produces the maximum amount of inlier points will be treated as best homography.

Let u represent the probability that any selected data point is an inlier and v = 1 – u, the probability of observing an outlier. N iterations of the minimum number of points denoted m are required, where

$$1-p=(1-u^m)^N \tag{1}$$

and thus, with some manipulation,

$$N=\frac{log(1-p)}{log(1-(1-v)^m)} \tag{2}$$

2.6 Image Warping and Blending

Any of the shapes in the image have significantly distorted then, Image warping may be used to correct the distortion. When an image is got transformed from one domain to other, Pure warping is nothing, but the points are mapped to points without changing the colors and mathematically it is from part of the plane to plane. If the function is injective the original can be reconstructed. Similarly, if the function is a bijection any image can be inversely transformed. The last step is to wrap and blend all the input images to an output composite mosaic (panorama). Finally, the pixels colors in the overlapped region of the images are blended to avoid the seams.

3 Results and Discussion

The proposed model is tested on three datasets in Python software having 32-bit and has been executed in system with configuration i4 processor, 8 GB RAM, 2 GB cache memory and 2.8GHz processor. A smoothing filter is used in this experiment to perform image warping. The seams that arise because of image stitching can be overcome using this filter. As the filter size increases, the smoothening will increase and vice versa. A higher filter size will introduce a lot of blur and lower filter size will fail to remove the sharp seams between the scene boundaries. Therefore, choosing an optimum filter size is challenging. We experimented by taking different filter sizes and found that a filter size of 40 is good enough to give a better mosaiced image. The model is compared with three different feature extractors popularly used in image mosaicing or image stitching algorithms, namely, SIFT, ORB and BRISK. We compare their performance in terms of the number of run time and the number of key features they use. The results are tabulated in Tables 1, 2 and 3 respectively.

Table 1. Comparison of Proposed model with different state-of-the-art method for dataset 1

Model	Dataset 1	Key features detected		Number of good matches	Time elapsed in seconds
		Image1	Image 2		
State-of-the-art model [9]	SIFT	1257	1491	569	0.1039
	BRISK	2062	2360	619	0.2392
	ORB	500	500	62	0.0571
Proposed Model	SIFT_hist	1257	1457	466	0.1731
	BRISK_hist	2062	2614	548	0.2654
	ORB_hist	500	500	59	0.0836

Table 2. Comparison of Proposed model with different state-of-the-art method for dataset 2

Model	Dataset 2	Key features detected		Number of good matches	Time elapsed in seconds
		Image1	Image 2		
State-of-the-art model [9]	SIFT	4239	5346	1317	0.5741
	BRISK	6730	8446	1371	0.9783
	ORB	500	500	100	0.2
Proposed Model	SIFT_hist	4239	4897	1297	0.6855
	BRISK_hist	6730	7076	1327	1.5911
	ORB_hist	500	500	99	0.3586

Table 3. Comparison of Proposed model with different state-of-the-art method for dataset 3

Model	Dataset 3	Key features detected		Number of good matches	Time elapsed in seconds
		Image1	Image 2		
State-of-the-art model [9]	SIFT	8726	9502	1683	1.2462
	BRISK	14821	19148	2362	4.7736
	ORB	500	500	160	0.3617
Proposed Model	SIFT_hist	8726	9196	1656	2.3920
	BRISK_hist	14821	19696	2303	6.1949
	ORB_hist	500	500	164	0.5727

From the above tables, it is observed and recorded that the ORB_hist is the best feature extractors among the state-of-the-art feature extractors. It uses minimum key features to match the images and generates panoramic images that are invariant to shift and rotation. The results are available in less time. Also, though the number of good matches is less compared to the other two feature extractors, these feature matches are sufficient to give a good panoramic image. Using histogram equalization module to remove any intensity variation between the scenes is necessary. Though we see that the results have overhead of time it is still a good pre-processing step when dealing with mosaicing of images taken from satellites, microscopes etc., where the intensities have vast inter-image and intra-image variabilities.

4 Conclusion

In this work, the right image is histogram equalized to the left image. The SIFT, ORB and BRISK feature descriptors are used to extract the key features of the images. Then the KNN matching technique is used to match the key points of the images. The RANSAC algorithm is applied on the matched features to compute the camera motion. Finally, the image warping process is performed with smoothing filter having size 40x40 to obtain the panorama image. The model is tested on three datasets to compute the performance. The ORB with HE performs better results with the minimum 500 key features in 0.0836 seconds of runtime when compared to the other state-of-the-art feature descriptors. In future, the model can be developed using fusion approaches for available spatial and frequency domain techniques.

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