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Feature-based Automatic Image Stitching Using SIFT, KNN and RANSAC

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ABSTRACT

Image panorama is a process of combining two or more images to form one single image. Image stitching is a process of creating image panorama from a set of images with overlapped fields. Image stitching faces many challenges such as images corrupted by noise, indexing a large number of images, high image resolution, and presence of parallax and scene motion. The problem in eliminating visible seam is also another challenge. To obtain a wide seamless panorama, this paper implemented a feature-based automatic image stitching algorithm. The image stitching model consists of five stages: image registration, features detection, feature matching, Homography estimation, and image blending. A method of creating a seamless image panorama was introduced where the scale-invariant features transform (SIFT) was used for image feature extraction, the K-nearest neighbor algorithm for feature matching, the Random sample consensus (RANSAC) for image warping calculating homography and the weighted matrix was intended for image blending. Three (3) sets of source images were used to test for stitching demo. The effectiveness of the stitching method was defined by comparing the resulting panorama to a predicted reference image using the percent image similarity defined as the proportion between the matches found and keypoints. For all of the testing sets, the resulting percent similarity with respect to the reference image ranges from 12-18%. This is due to the fact that high-quality images (i.e. high number of pixels) have thousands of features - hence, thousands of keypoints while low-quality images may have only a few hundreds.

Key words: Image Stitching, Panorama, SIFT, KNN, RANSAC

1. INTRODUCTION

Image stitching is widely used for producing today's digital maps and satellite photos. It is a process of creating image panorama from a set of images with overlapped fields. Algorithms are used for aligning images and stitching them into a seamless panorama. Image stitching first originated in photogrammetry fields. Manually intensive methods based on surveyed ground control points or manually registered tie points have long been used to register aerial photos into large scale photo mosaics [1]. One important progress is the development of a bundle adjustment algorithm that solves for the locations and positions of cameras simultaneously. Overlapped images can also be combined to minimize the introduction of seams [2]. This became a good focus of many other research works which included two different basic ideas. One is by minimizing pixel dissimilarities [3] and gradient descent methods [4]. Another implementation is by extracting a set of features and matches them to each other. Such feature-based methods automatically discover the overlapping relationship between the set of unordered images.

Image stitching faces many challenges such as images corrupted by noise, indexing a large number of images, high image resolution, and the presence of parallax and scene motion [5], and also the problem in eliminating visible seam [6]. The goal of this paper is to obtain a seamless image panorama by implementing an automatic image stitching mechanism using two input images based on feature extraction and to determine the effectiveness of the stitching method using the percent similarity of the resulting panorama to a predicted reference image. The reference image is the region of interest (ROI) wherein the width is based on the combined width of the two source images less the overlap width of source image 2 to source image 1(i.e. a 50 cm overlap width).

The paper is organized as follows. Section 1 introduces the area of concentration and motivation of the research. Related works concentrated on image processing and stitching are discussed in Section 2. Section 3 presents the methodology of the research. Tests and results are presented in Section 4. Finally, conclusion and future work are discussed in Section 5.

2. RELATED WORKS

Many approaches have been proposed for image stitching over decades ago. A multiple constraint corner matching approach was proposed in [7] and the result was a faster image stitching. This lessened the number of iterations of a traditional RANSAC algorithm. A feature-based alignment algorithm and blending algorithm has also been proposed by [8] which successfully generate panorama image by removing the transition in the aligned images. Meanwhile, an adaptive uniform distribution SURF algorithm for image stitching by reduced the computation complexity suitable for image matching [9]. An image mosaic algorithm is based on a random corner method [11]. The study avoided corner redundancy and removed false matched corner pair effectively. To overcome the limitations in stitching blurred images, a feature-based algorithm that uses overlapped blurred image pairs for kernel estimation is done [6]. The based de-blurring algorithm was based on the projective warping model. A new algorithm for image registration and stitching was also customized to generate single images of surfaces, which cannot be captured by a single photo [12]. A seam inserting operation can be adopted and implement an adaptive color blending algorithm that produces a stitched image without the visible artifacts [13]. The low-complexity image stitching algorithm also allows users to generate a good-quality panoramic image even the photos have rotation and zooming actions [14]. Feature-based image registration algorithm is with limited computing power for mobile devices of [15].

3. METHODOLOGY

In this paper, the image stitching model used consists of five stages: image registration, features Extraction, feature matching, Homography estimation, and image blending as shown in Figure. 1.

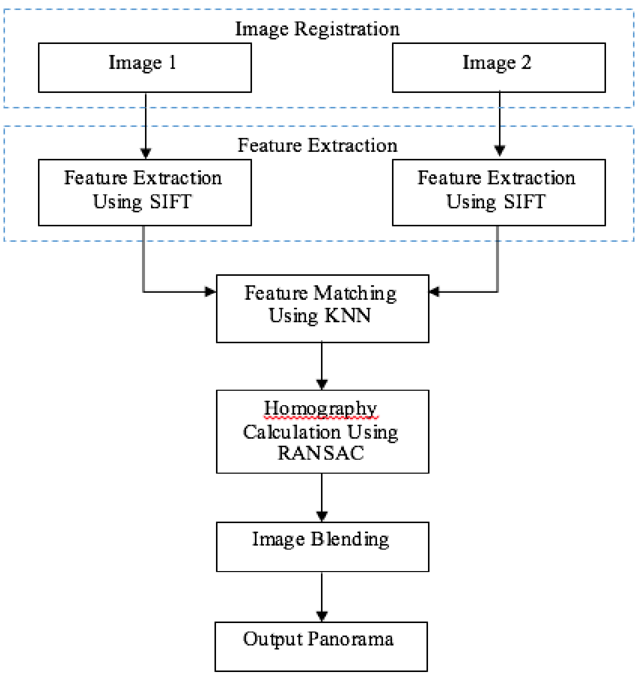
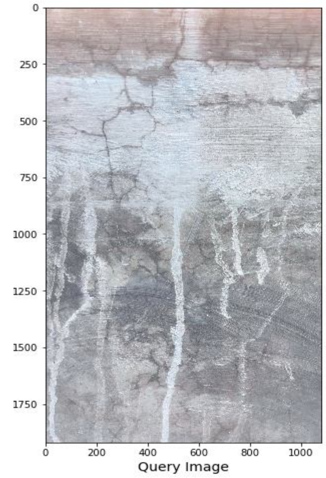


Figure 1: The block diagram of the stitching method.

A. Image Registration

In image registration, images are acquired and identified as the set of pair images to be used in the image stitching process. Figure 2 and Figure 3 were used as the test images used in the system.



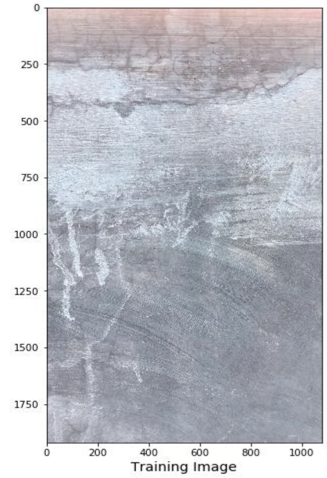


Figure 2: Test Image 1 **Figure 3:** Test Image 2

B. Features Extraction

The second stage is feature detection. Features are the elements in the images that used to match in the image stitching. there are many different methods for feature detection [16]: Harris corner detector, scale-invariant features transform (SIFT), speeded up robust features (SURF), Oriented fast and rotated BRIEF (ORB) and so on. SURF is partly inspired by the SIFT descriptor. The standard SURF is several times faster than SIFT. In this paper, the classic SIFT was used to implement feature extraction. There are four core steps for SIFT algorithms: scale-space extrema detection, keypoint localization, orientation assignment, and keypoint descriptor.

The first step is to generate an image pyramid from each image using Gaussian blurring and then calculate the Difference of Gaussian (DOG) pyramid by subtracting neighbor images from the blurred out image. If the DOG is found, images will be searched for local extrema. Extrema detection produces a set of potential key points. But some of them are unstable. Some constraints should be applied to filter some points. The first extrema are rejected if the intensity is less than a given threshold value. Second is the elimination of low-contrast key points and some points which are located at the edge. The next step is the keypoint orientation assignment. In this step, each key point will be assigned an orientation, based on the local image gradient directions followed by Keypoint descriptor generation.

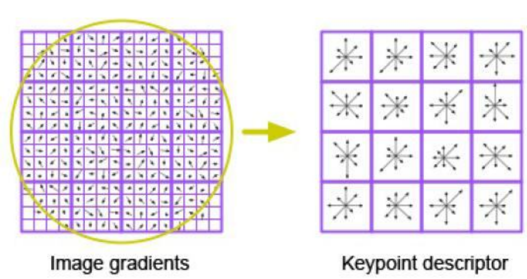
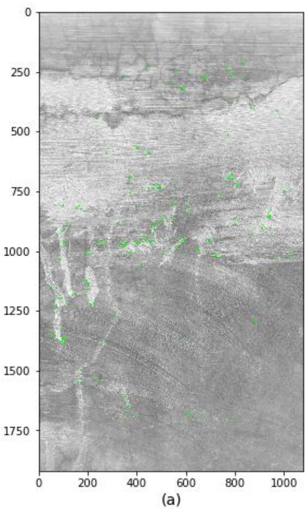


Figure 4: The Keypoint descriptor generation.

Around the reference keypoint, a neighborhood is taken to determine the gradient magnitude and direction indicated by the overlaid circle as shown in Figure 4. This neighborhood is then divided into 16 sub-blocks, orientation histograms created from each sub-blocks are accumulated then summarized it over the content of the 4x4 sub-regions. The accumulated gradient magnitude near the region direction is represented by the length of each arrow. The original images with detected key points are displayed in Figure 5 and Figure 6.



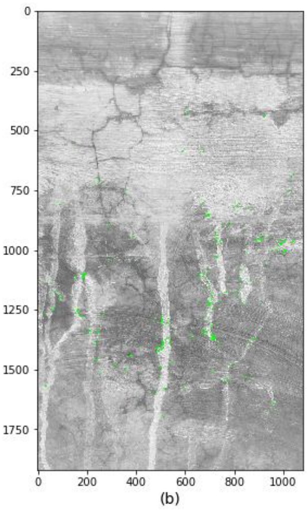


Figure 5: Keypoints in Image 1 **Figure 6:** Keypoint in Image 2

C. Feature Matching

Upon obtaining the descriptors for images, they pair them by some matching methods. For feature matching, we can use two types of matcher: Brute Force Matcher and KNN (K-Nearest Neighbors). Brute Force calculates the distance between two points using the Euclidean distance. Thus, for every descriptor in image 1, it returns the closest descriptor in image 2 and vice versa. Brute force returns the single best match for a given descriptor.

On the other hand, KNN (k-Nearest Neighbors) is used when to consider more than one candidate match. KNN returns the k best matches, instead of returning the single best match for a given descriptor. K-nearest neighbors (KNN) was hereby used in this paper in matching between keypoints of two images. Having K is equal to 2 means that for one key point in the first image, two matches are found in the second image. In some cases, the distance between the second-best match and the best matches may be very close due to noise – hence, the ratio test is applied. The ratio of closest distance to the second closest distance is calculated.

The match is acceptable if the resulting ratio is less than the threshold value. In this work, the ratio is set as 0.85. It means that if it’s a good match, the closest match distance should be “smaller enough” than the second closest match distance. The matching image is presented in Figure. 7.

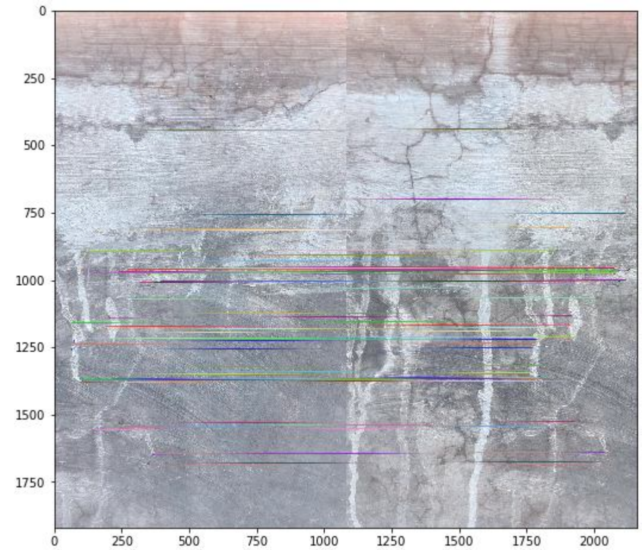


Figure 7: Matching Image

D. Homography Calculation Using RANSAC

As seen in Figure 7, some features pairs between the two images are correct while some other pairs are not. The incorrect pairs should not be taken into homography calculation due to the inclusion of errors in the final result. In order to get rid of such incorrect pairs, random sample consensus is applied. The incorrect matching pairs are called the “outliers” and the correct matching pairs are called “inliers” in RANSAC algorithms. The RANSAC is hereby used in this work to select a subset of inliers matching pairs and discard the outliers.

E. Image Blending

Once the homography matrix is obtained, it can be applied to the source image to implement warping. But this may result in not obtaining a perfect and seamless panorama image as seen in Figure 8.

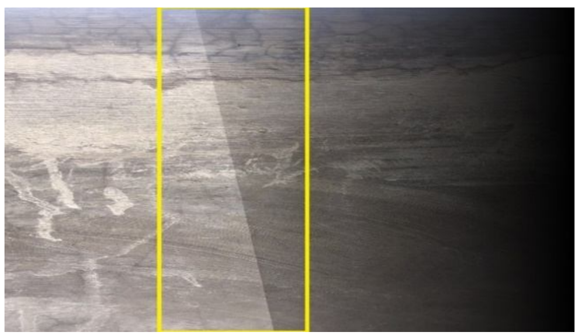


Figure 8: A Rough Panorama Result

In Figure. 8, there are obvious distortions in the overlapped fields of the images. The color and light are also uneven because the exposure time of the shutters and white balance control of the cameras change when capturing the same scene from different perspectives. Thus, it’s necessary to perform image blending.

A weighted matrix is created as a mask to smooth the discontinuities between the two overlapped pictures. Actually, this mask is a matrix with the same size as the output panorama image which has two versions for this mask. Dealing with the seam in the overlapped region, the region on the left side and the right side of the seam invariant should be kept and modify the overlapped part. Hence, the mask matrix has a so-called smoothing window.

First, multiply image 1 and the left version mask element by element. Then homography warps image 2 and multiply it with the right version mask element by element. These are then concatenated together to obtain the final image panorama. Figure 9 shows the final image panorama.

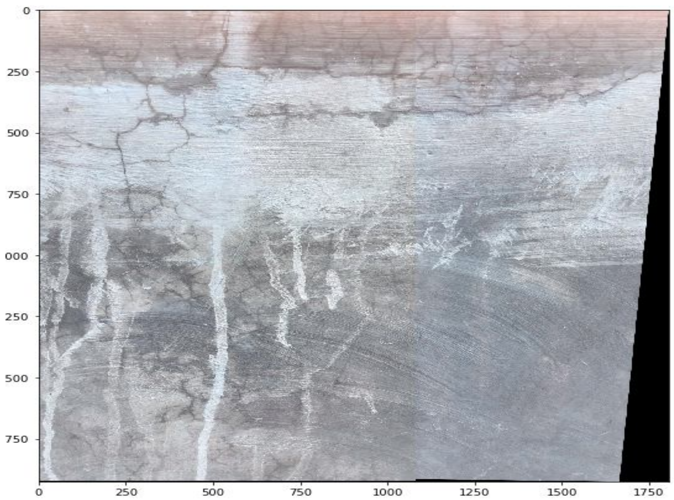


Figure 9: Final Panorama

4. TESTS AND RESULTS

Three (3) sets of source images were used to test for stitching demo. To each of the sets of source images, the iPhone 6 camera was used to capture the images. Figure 10 shows the schematic capturing of the source image. And Table 1 shows the image area and resolution of the input image based on the camera distance from the wall of 300 cm and an overlap distance of 50 cm between the query image and the training image.

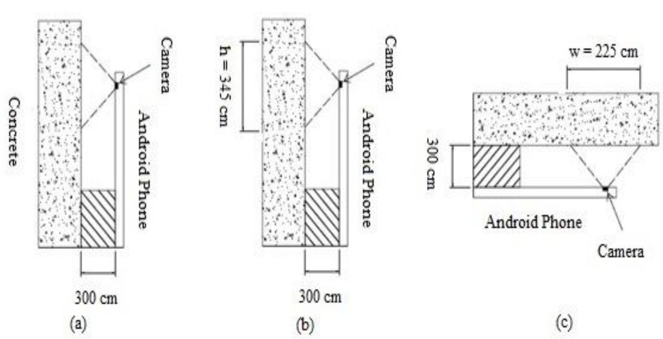


Figure 10. Source image schematic capturing: (a) Distance between the camera of an android phone and the concrete wall, (b) the height of the source image, and (c) the width of the source image.

Table 1: Shows the image area and resolution of the input image based on the given camera distance from the wall.

Set	Resolution	Area (w * l) (cm x cm)	Distance from the Wall (cm)
1	1080 x 1920	225 x 345	300
2	1080 x 1920	225 x 345	300
3	1080 x 1920	225 x 345	300

Applying the Feature-based Automatic Image Stitching Using SIFT, KNN and RANSAC into the input images with an overlap distance of 50 cm, the resulting images are as follows (Table2):

Table 2: Shows the input image (query and training image) and the resulting stitched image.

Set	Query Image	Training Image	Stitched Image
1			
2			
3			

To determine the effectiveness of the stitching method, the resulting stitched image is compared to the reference image. The reference image is the region of interest (ROI) wherein the width is based on the combined width of the two source images less the overlap width of source image 2 to source image 1(i.e. a 50 cm overlap width.).

Figure 11 shows the schematic capturing of the reference image (ROI), Table 5 shows the image area and resolution of the reference image based on the camera distance from the wall of 450cm.

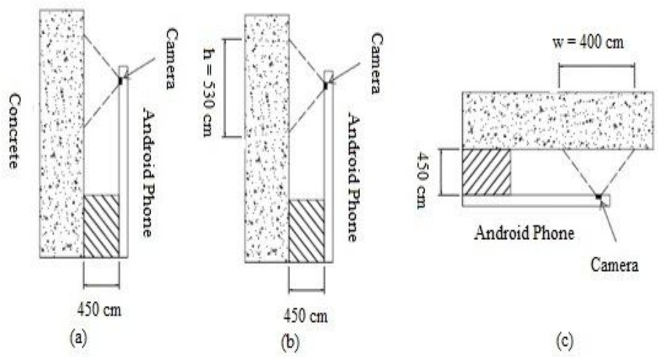


Figure 11: Reference image schematic capturing: (a) Distance between the camera and the concrete wall, (b) the height of the image, and (c) the width of the image.

Table 3: Shows the image area and resolution of the input image based on the given camera distance from the wall.

Set	Resolution	Area (cm x cm)	Distance (cm)	Reference Image
1	1080 x 1920	450 x 530	450	
2	1080 x 1920	450 x 530	450	
3	1080 x 1920	450 x 530	450	

Based on the features of the two images, a percentage of similarity can be defined ranging from 0-100, where 0 it means completely different while 100 equal, even if they have different sizes. Table 5 and Figure. 12 presents the comparative results. The following plots depicts the comparative result between similarities of Resulting Stiched Image and Region of Interest (ROI), based on keypoints and good matches found.

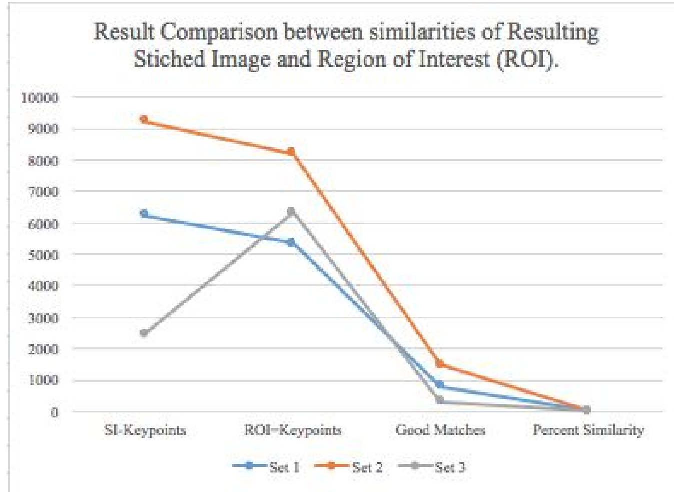


Figure 12.:Result Comparison between similarities of Resulting Stitched Image and Region of Interest (ROI).

Table 5: Comparison between the Percent Similarity of the Resulting Stitched Image and the Region of Interest (ROI).

	Feature Matching (Keypoints Detection)			**Percent Similarity**
Set NO.	Stitched Image	Reference Image	Good Matches	%
1	6229	5351	813	15.1934
2	9229	8193	1469	17.9299
3	2457	6328	300	12.2100

Based on the percent similarities presented in Table 5 and Figure 12, high quality image (i.e. high number of pixels) is present and may have thousands of features - hence, thousands of keypoints while low quality images may have only a few hundreds. The percent similarity can be determined by proportion between the matches found and keypoints.

By checking the number of keypoints of both images, the number of the images having less keypoints is taken. The number of good matches is divided by the number of keypoints. The result is a value ranging between 0-100 multiplied by 100 to derive a percentage.

5. CONCLUSIONS

In this paper, a method of creating a seamless image panorama was introduced - the feature-based automatic image stitching using SIFT, KNN, and RANSAC. The method uses the scale-invariant features transform (SIFT) for image feature extraction; the K-nearest neighbor algorithm was used for feature matching, and for image warping, Random sample consensus (RANSAC) was used to calculate homography. A weighted matrix was applied for image blending.

The effectiveness of the stitching method was defined by comparing the resulting panorama to a predicted reference image using the percent image similarity defined as the proportion between the matches found and keypoints of the images being compared. Based on the result, the effectiveness of the image stitching method depends on the quality of the resulting stitched image since high-quality image (i.e. high number of pixels) have thousands of features - hence, thousands of keypoints while low-quality images may have only a few hundreds.

For future enhancement, the algorithm needs improvement in its robustness in stitching 3 or more images.

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