Panoramic Image Stitching Techniques Based on SURF and Singular Value Decomposition

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Abstract. The fundamental goal of stitching images is to discover a group of images of a single scene, combine them to form one image for a wide scene. The handheld camera has limited resolution and a narrow field of view. Image stitching faces many challenges such as alignment of image, illumination variation, bad lighting, different scale, and low resolution resulting from stitching. The objective of this paper is to produce a high-resolution panorama in different uncontrolled environments. The suggested method starts by detecting the overlapping areas based on detecting the features extracted by the Speeded-Up Robust Features (SURF) algorithm and Singular Value Decomposition (SVD). Images are automatically aligned based on discovering the geometric relation sips among the images, then images concatenated to create a panoramic image. The suggested algorithm was experimentally tested with different uncontrolled environments such as different resolutions, different image sizes, different numbers of input images, different illumination, and bad lighting. The results showed that the proposed algorithm could stitch correctly with a different overlapping area up to 20% and sometimes more for the images obtained by a wide lens with a different wide-angle. The results were promised and dependable, and the tests prove the ability of the proposed algorithm to solve many image stitching challenges.

Keywords: Panorama · Speeded-up robust features · Singular value decomposition · Image stitching · Image alignment

1 Introduction

Image stitching is a process to combine a sequence of images, mutually having overlapping areas, resulting in a seamless, smooth panoramic image. The handheld camera has limited resolution and small field-of-view, while the image stitching can get high-resolution and high-quality panorama by using handheld equipment. Image stitching has become a hot spot in the field of computer vision, image processing, and computer graphics [1].

A. M. Al-Bakry et al. (Eds.): NTICT 2021, CCIS 1511, pp. 63–86, 2021.
https://doi.org/10.1007/978-3-030-93417-0_5

Aligning and stitching images together is one of the oldest and most widely used techniques in computer vision. Algorithms for image stitching create the high-resolution photos used to create digital maps and satellite images. Additionally, they are included with the majority of current digital cameras and can be used to create stunning ultra-wide-angle panoramas [2]. Since the dawn of photography, combining smaller images to create high-resolution images has been popular [3]. The principle behind image stitching is to combine multiple images into a high-resolution panoramic image based on the overlaps between the images. A specialized form of image known as image stitching has become increasingly common, especially in the making of panoramic images.

To achieve seamless results, there should be nearly exact overlaps between images for stitching and identical exposures. Stitching is not possible if the images do not share a common region. The images of the same scene will have varying intensities, scales, and orientations, and the stitching should work or at the very least produce an output that is visually appealing [5].

The image stitching problem can be divided into two distinct areas of research: image alignment and image stitching. The researchers try to discover the geometric relationships among the images and how the image rotation and the area of images overlapping effects the alignment process. On the other side, working in an uncontrolled environment has a high effect on the panorama resolution and stitching performance. Many other problems affect the stitching, such as blurring or ghosting caused by scene and parallax movement, different image exposures as well as distortions caused by camera lens so that seamless, high-quality panoramas can be achieved [2].

Typically, the image stitching process is divided into three stages: registration, merging, and blending. During image registration, multiple images are compared to determine which translations can be used for image alignment. Following registration, these images are stitched together to create a single image. The purpose of image merging is to obscure the transition between adjacent images visually. In the majority of cases, adjacent image edges exhibit undesirable intensity discrepancies. These intensity variations are present even when the registration of two images appears to be nearly perfect. A blending algorithm is used to eliminate these effects and improve the visual quality of the composite image. The purpose of blending is to determine the final value of a pixel in an area where two images overlap [4].

Several algorithms are introduced to accomplish image stitching. The traditional algorithms perform pixel-by-pixel registration (Direct method), which employs some error criteria to determine the best registration, i.e. the registration with the lowest error value is the best. These methods are slow down and occasionally do not produce the best results. The feature-based registration methods identify distinctive features in each image and then match them efficiently to establish correspondences between pairs of images to determine the approximate motion model, such as SURF&SVD. Feature-based approaches have the advantage of being more resistant to scene movement and potentially faster; when implemented correctly, common feature points are used to establish the relationships between the images that enable automated stitching.

The rest of the paper includes related works in section two, while the types of feature extraction and points are introduced in section three. Section four focuses on the methodology. Section five introduce the results, and finally, section six assigns to the conclusion.

2 Related Works

Several techniques were suggested previously, and many researchers work in the field of image stitching. This section is focused on the reviews of previous methods that have worked in this field of study. Some of them are:

T. Zhang, et al. (2020) The authors proposed an improved SURF algorithm. The feature points are extracted through the Hessian matrix, and then the circular neighborhood of the feature points is used for feature description. Each wave point is used to discover a descriptor for every feature point; Random Sample Consensus (RANSAC) can be used to get rid of all unwanted or unmatched points. In comparison to the conventional SURF algorithm, this algorithm benefits from good speed, full use, and higher accuracy of gray information and detailed information [6]. The accuracy of the stitching was 83.75%, which is considered good, but it needs more time.

Qi, et al. (2019) The authors suggested an improved SURF feature extraction method. The retrieval and recording of images is the core of the image stitching, which contributes directly to the quality of the stitching. Tackling the issue of unequal distribution of images and image stitching. In this proposed, the BRIEF operator in the ORB algorithm performs the rotation shift-invariance. The European pull distance was later used to measure the similarity, and the KNN algorithm is used to calculate the rough features matching. Finally, the larger distance threshold is used to delete the corresponding pair, and the RANSAC algorithm is then used for cleaning. Experiments show that the algorithm proposed is good in real-time but it did not solve the problem of computing in extracting the descriptor of the features, and the mismatch of the similarity of the descriptors, so it is not possible to stitch the multi-images and high-resolution [8].

Shreevastava, et al. (2019) The authors proposed a mismatching point elimination algorithm based on the angle cosine and RANSAC algorithms to address the ORB algorithm's high number of mismatches and low accuracy. Experiments demonstrate that the improved algorithm significantly improves accuracy and is more efficient than the established algorithms SIFT and SURF, making it applicable to various applications requiring high precision and real-time performance. However, it did not solve the problem of stitching the image at the condition of poor lighting, and when there is variation in the geometrical images due to the small number of matching features [9].

M. Wang, et al. (2017) The authors address that the SIFT and SURF features face a problem of long time-consuming. The authors proposed a new image-stitching algorithm using ORB features (Oriented FAST and Rotated BRIEF) to solve the time problem. FAST is used to extract the ORB feature points with directional information, de-scribed by BRIEF. Feature extracting and matching. Also, the false matching points were removed by using the RANSAC algorithm. Lastly, the image blending speeds up by using the weighted average method. The authors proved that image stitching by using the proposed algorithm have the same effect as that of the SIFT and SURF algorithms in terms of results, this method did not solve the problem of illumination variation for the input images, noise, and the difference in the direction of the images, this is due to the instability of rotation [10].

3 Contribution

1. In this method, SVD is used to extract features, and this is the first method used SVD in panorama generation.
2. Suggest a hybrid method that combined SVD and SURF.
3. Reduce time for panorama generates with any number of input images.
4. Generation panorama is robust for image noise, illumination variation, poor illumination.
5. Reduce the effect of the seam line problem as in the previous works.

4 Image Stitching System

The image stitching system accepts two or more input images and outputs the stitched image. The main general steps of image stitching are shown in Fig. 1.

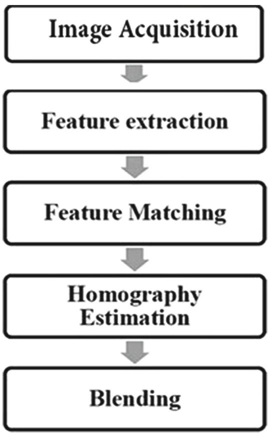

Fig. 1. Block diagram of the general image stitching process

4.1 Image Acquisition

Since the proposed algorithm is based on using the feature-based algorithm, the best features and points must be obtained from the images, and precisely it depends on the specification of the device capturing images. Capturing the image should take care of how to shoot with an angle and view of an entire scene. This helps to get a better result and reduce errors and problems of the resulting panoramic image. Some notes have to be considered when capturing the images. Some of them are:

1. Keep capturing the same scene flat to have the same alignment of the images through a tripod with the lens at its center as in Fig. 2.
2. Images better have the same balance and exposure, especially the white color that represents the lighting, to avoid changing the surfaces of the images and get a good merger between the overlapping areas.
3. Avoid using a lens with an extensive focal length. Therefore, the images will be subjected to high distortion in the lens and may cause alignment problems. As a result, it is recommended to use a focal length of 35 mm or slightly higher.
4. Maintaining the overlap area at 20% or more between every two images as in Fig. 2. The greater the overlap area between the pairs of images, the better the result of stitching will be for the panoramic image.

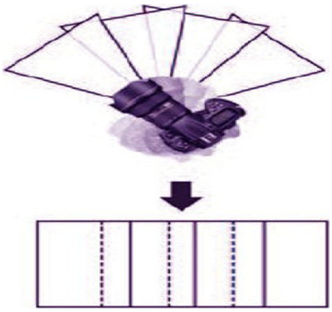

Fig. 2. The process of Image acquiring of four images [19]

4.2 Features Extraction

Features detection is used within computer vision systems to extract features of an image. Detected features are used by motion detection, tracking, panorama stitching, and object recognition system. Points are the simplest features that can be detected. They can be found by corner detection algorithms [14]. The essential characteristics desired in feature extractors are their distinctiveness, accurate and robust keypoint localization, robustness to noise, invariance to orientation, shift, scale, changes in viewpoint, illuminations, occlusions, repeatability, and computationally effectiveness. The most precious property of a feature detector is its repeatability which is the reliability of a detector for finding the same physical feature points under different viewing conditions. The three feature types are Corners, Edges, and uniform intensity regions, as shown in Fig. 3.

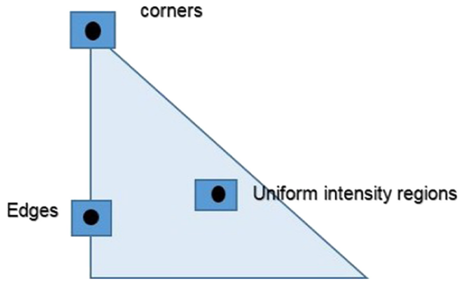

Fig. 3. Type of feature

Finding the correct feature points is critical for performing the correct stitching [12]. It is the first step, and thus it is critical to select the correct detector for this point. Some of these feature detections is:

Singular Value Decomposition

The Singular Value Decomposition is a focus on linear algebra, it gives three matrices as shown in Fig. 4.

$$A = USV^T \tag{1}$$

Where [13].

- U is an m × n matrix with orthonormal columns.
- S is an n × n diagonal matrix with non-negative entries.
- V^T is an n × n orthonormal matrix.

The diagonal values of S are called the Singular Values of A. S is the summation of the diagonal entities λ1, λ2….. which represent the singular vector (called singular values) of a matrix (A) So,

$A = \lambda 1\ U1\ V1^T + \lambda 2\ U2\ V2^T + \ldots + \lambda r\ Ur\ Vr^T$.

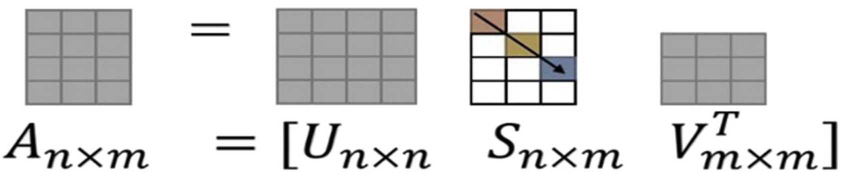

Fig. 4. The resulting matrices from SVD transformation [13]

4.3 Speeded up Robust Features

Speeded up robust features is a scale and rotation invariant interest points detector and descriptor that is used in computer vision works like 3D reconstruction or object recognition. SURF uses a Haar wavelet approximation of the determinant of the Hessian matrix; its descriptor is a collection of Harr wavelet responses around the interesting point. The local area is divided into a 4 × 4 grid. The x and y components of the Harr wavelet response and the absolute value are calculated for each quadrant of the local area. Concatenating these 4 × 4 subregions produce a descriptor vector of length 64 for each interest point. This descriptor is distinctive and robust to noise, detection displacement, and geometric and photometric deformation [14]; it focuses on the scale and in-standard rotation-invariant detectors and descriptors. These seem to offer a good compromise between feature complexity and robustness to commonly occurring photometric deformations [15]. Given a point K = (x, y) in an image I, the Hessian matrix ‘H(x, σ) in x at scale σ weighted with a Gaussian is defined as follows[14].

$$\mathrm{H}(\mathrm{K}, \sigma) = \begin{matrix} Lxx(K, \sigma) & Lxy(K, \sigma) \\ Lxy(K, \sigma) & Lyy(K, \sigma) \end{matrix} \tag{2}$$

Where Lxx(K,σ) is the convolution of the Gaussian second-order derivative $\frac{\partial 2}{\partial x 2}$ g (σ) with the image I in point x, and similarly for Lxy(K,σ) and Lxy(K,σ).

After extracting the points from the Hessian determinant, the first step for the extraction of the point and orientation along the orientation selected. The size of this window is the 20s [16], where (s) the scale at which the interesting point was detected. Examples of such square regions are illustrated in Fig. 5(A) is preserved important spatial information. For each sub-region, Haar wavelet responses are computed as shown in Fig. 5(B). The dark parts have the weight –1 and the light parts + 1. Orientation assignment: a sliding window orientation of size π/3 detects the dominant orientation of the Gaussian weighted Haar wavelet responses at every sample point within a circular neighborhood around the interesting point, as shown in Fig. 5(C). To build the descriptor, an oriented quadratic grid with 4 × 4 square sub-regions is laid over the interesting point as shown in Fig. 5(D).

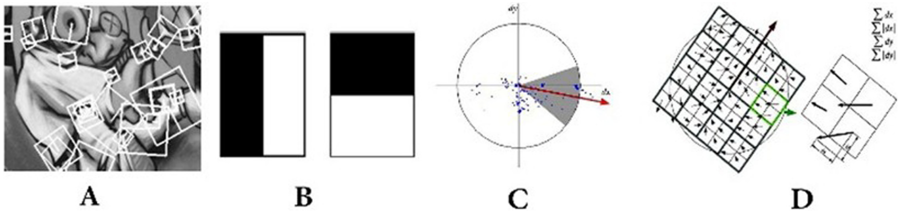

Fig. 5. Type (A) features obtained using Hessian-based detectors, (B) Haar wavelet (C) Orientation assignment (D) To build the descriptor [14]

The primary objective of using integral images in SURF is to reduce the time required to compute key points.They allow the computation of convolution filters of the box type to be achieved in a short amount of time. An integral image denoted I (x, y) at location (x, y) contains the number of the pixel's values above and to the left of (x, y) according to Eq. 3 [14].

$$I(x,y) = \sum\nolimits_{x',y' \leq x,y} I(x',y'). \tag{3}$$

4.4 Features Matching

Features matching is the process to find corresponding features in two or more different views of the same scene. There are a lot of approaches for matching features. Generally, they can be classified into two categories: region-based matching and feature-based matching. The proposed algorithm will use feature-based matching. After the matching pairs are known, it will return the dependent points to these features and then estimate Geometric Transform [17]. When matching, there will be one feature in the first image and more than one feature in the second image. To solve this problem, we use the unique feature as in Fig. 6.

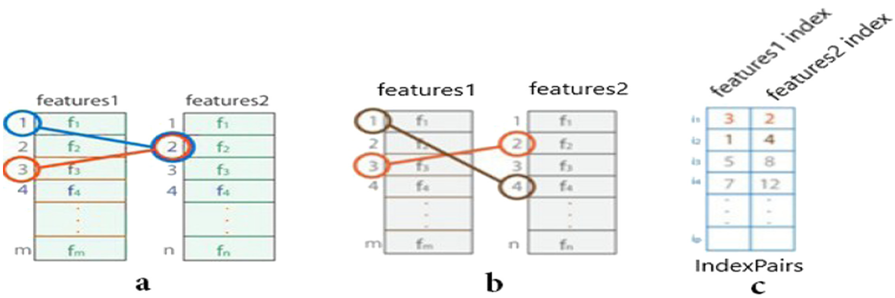

Fig. 6. The matching process: a) matching features1 to features2, b) Choose the unique feature in the case of the similarity of more than one. c) keeps the best match within the identical index pairs

4.5 Homography Estimation

A homography is an invertible transformation from the real projective plane to the projective plane that maps straight lines. The purpose of homography is to specify a point-by-point mapping from the locations of pixels in one image to their corresponding pixels in another image, as illustrated in Fig. 7. This mapping is performed on the assumption that the two images are planar: The two images' points are mapped, assuming that the object being imaged is planar [18]. Two images are related by a homography only if both images are viewing the same plane from a different angle; the Camera may be rotated.

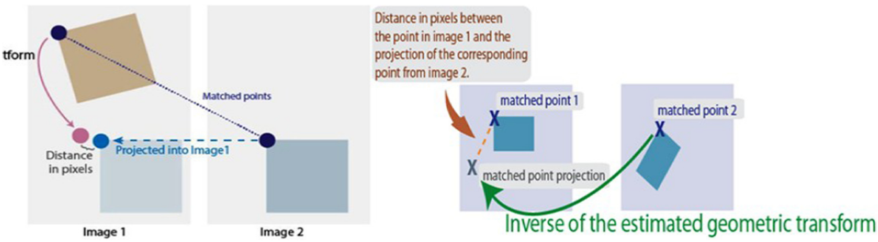

Fig. 7. The process of dropping and dragging points through the space between pixels and the geometry transformation.

Aligning the image requires estimating the geometric transform between each matched pair, which is then used for alignment.

The projection of point X' on a rotating image can be calculated as [19]

$$x' = [K][Rt]X \tag{4}$$

where K is the calibration matrix, R is the rotation matrix, t is the translation vector and X is the world coordinates.

We now have all of the images with a fixed rotational axis, and the position of the P-camera, as shown in Fig. 8, is identical for the acquired images $I_1$and.I_2.

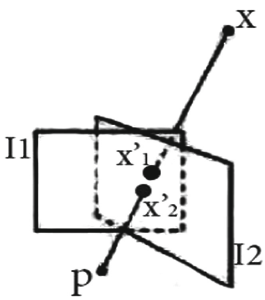

Fig. 8. Aligning two rotational images [19]

As illustrated in Fig. 8, the two images were taken in the same position with no translation; the matching pair can be rewritten as [19]:

$$\mathrm{x}'1 = K1R1X \tag{5}$$

$$\mathrm{x}'2 = K2R2X \tag{6}$$

By combining Eq. (5) and (6), the relationship between x'1 and x'2 is described as

$$x'2 = K2R2R1TK1 - 1x'1 \ Or \ x'2 = Tx'1 \tag{7}$$

Where T = $K_2R_2\ R_1^T\ K_1^{-1}$ is known as the transformation matrix. Equation (7) is applied to each point of the identical pairs for each point in the I(n-1) and I(n) to estimate the projection between the two images. The equation can be written for all the engineering estimate completely in the form.

$$I(n) = T(n)I(n-1) \tag{8}$$

The transformation between I (n) and I (n-1) is estimated by T(n).

The hierarchy of 2D linear transformations has several types as shown in Fig. 9, but the most commonly used in panoramas are similarly, affine and projective. The latter is chosen because it maintains collinearity, synchronization, and connection order and is dependent on the maximum number of congruent point pairs and has a minimum of (4), while affine (3), and likewise (2). And the exclusion of non-internal outliers using the RANSAC algorithm.

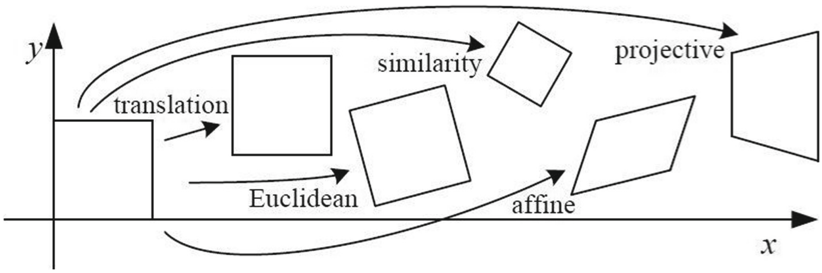

Fig. 9. Different transformations [3]

5 Blending and Composing

The algorithm's final stage is image blending and composition. Before aligning all the images, a 2-D spatial space must be created so that all the images can be aligned in a loop using the transformation matrix. After aligning the images, the image edges must be blended to produce a smooth view. The linear gradient blending technique is used to accomplish this task in this algorithm because it is quicker and produces more accurate results. Gradient blending may be customized to deal with complex alignments that occur when images are rotated or taken in perspective [19]. This is an easy-to-use approach that works well. It produces a linear gradient by shifting the alpha channel from one image's center to another image's center. The term “blend image” is defined as: [19].

$$I_{\text{blend}} = I_{\text{Left}} + (1-)I_{\text{Right}} \tag{9}$$

Where is the gradient weight, which can be any value between 0 and 1, and I_{Left} and I_{Right} are the two images to be blended. After aligning and blending all of the images in the picture package, the panoramic image is eventually composed, as shown in Fig. 10.

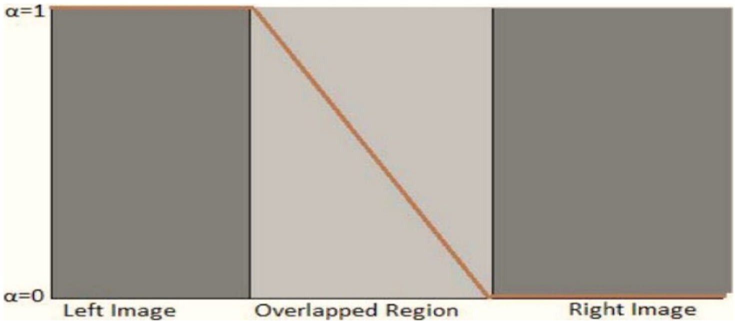

Fig. 10. Gradient blending in the overlapping area, α decreases from 1 to 0 [4].

6 Image Quality Metrics

Image quality measurement (IQM) plays an important role in evaluating the performance of image processing, where the image quality is defined as a property of the image to measure the degradation of the processed image by comparing it to an ideal image.

1. **Normalized Cross-Correlation (NCC):** a tool used to find the relation between two images, normally the source image and the degraded image. Formula to measure NCC is: [20].

$$NCC = \sum\nolimits_{i=1}^{N} \sum\nolimits_{j=1}^{m} \frac{(Aij*Bij)}{AIJ^2} \tag{10}$$

   Ideal Values = (1), The worst values are greater than (1).

2. **Structure Similarity Index (SSIM):** is defined as a function of luminance comparison, contrast, and structural information of images. The general formula of SSIM is:

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma} \tag{11}$$

   Where α, β, and γ are parameters that define the relative importance of each component, and:

$$\mathrm{l(x, y) = (2\mu_x\mu_y + C1)/(\mu_x^2 + \mu_y^2 + C1)} \tag{12}$$

$$\mathrm{c(x, y) = (2\sigma_x\sigma_y + C2)/\left(\sigma_x^2 + \sigma_y^2 + C2\right)} \tag{13}$$

$$\mathrm{s(x, y) = (\sigma_{xy} + C3)/(\sigma_x\sigma_y + C3)} \tag{14}$$

Where C1, C2, and C3 are constants introduced to avoid instabilities when the average pixel value $(\mu_x^2 + \mu_y^2)$ standard deviation $(\sigma_x^2 + \sigma_y^2)$ or $(\sigma_x + \sigma_y)$ is close to zero. SSIM (x, y) ranges from zero (completely different) to one (identical patches) [20].

1. **Perception-based Image Quality Evaluator (PIQUE):** This tool quantifies the distortion without the need for any training data. It relies on extracting local features for predicting quality. The general formula is [21].

$$\mathrm{PIQUE} = \frac{\left(\sum_{k=1}^{N^{SA}} D_{SK}\right) + C_1}{(N_{SA} + C_1)} \tag{15}$$

   The quality scale ranges, Excellent (0–20), Good (21–35), Fair (36–50), poor & Bad (51–100).
2. **Natural Image Quality Evaluator (NIQE):** It is used to measure the deviations from statistical regularities observed in natural images, it is a completely blind tool (not need reference image), NIQE formula is [22]

$$NIQE(D_{(v1,v2,\sum 1,\sum 2)})\sqrt{(v1 - v2)^T \left(\frac{\sum 1 + \sum 2}{2}\right)^{-1} (v1 - v2)} \tag{16}$$

   NIQE returned a non-negative value. Lower values of score reflect the better perceptual quality of image the input.
3. **Blind/Reference less Image Spatial Quality Evaluator (BRISQUE):** which extracts the point-wise statistics of local normalized luminance signals and measures image naturalness (or lack thereof) based on measured deviations from a natural image model, the general formula is [23]:

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C} \tag{17}$$

BRISQUE returned a nonnegative scalar value in the range of [0, 100], A low score value indicates high perceptual quality and a high score value indicates low perceptual quality [23].

7 Methodology

This section explains the proposed stitching method to get a panorama image based on SVD features extraction and the SURF method. The main processes of this proposal are: points detection, matching extracted features of points, and geometric transformation to create a panorama. The image stitching process to produce a clear and high-resolution panoramic image requires a set of steps, whether on a gray or color image as listed in Algorithm (1).

Algorithm 1: SVD-SUFT Stitching

Input: N images, where N number of images.
Output: Panorama image.

Begin:

1. Initialize the empty panorama image with width and height (P).
2. Read the first image from the image set.
3. Convert RGB images to grey images.
4. Detection points (poi) of a gray image by the SURF method.
5. Find extract features (fea) of image and points by SURF method to get new points and features.
6. Compute other features by using the SVD algorithm to get U, S, and V matrices of features.
7. Summation SURF features with SVD feathers.
8. Resize the height of the image according to (P).
9. Project the image in the (P).
10. Read the new images.
11. Repeat steps from steps 3 to 7.
12. Map extracted features of the first image with features of the current image using exhaustive feather matching, which relies on the distance between their features. Results are the index of mapped coordinates.
13. Find matched Points of corresponding points in the previous step.
14. Estimate the project transformation for the points from the previous step to the project on the panorama (P).
15. Resize the current image height according to (P).
16. Project the current image in the (P).
17. If there is another image to be stitching, go to step 10.
    output= panorama.

End

Step1 creates a zero-empty panoramic matrix, so the images are projected to their specific location. This is done by relying on the dimensions extracted from geometric transformations, and also it depends on the number of images that make the panorama and their sizes. The images are superimposed over others, ending with the last image of the panorama.

The first image will be read from the set of images. The input RGB image is converted into a gray-level image, as well as eliminating any noise and unwanted particles.

Unique and strong points such as the edges of the image or corners will be detected by SURF. Returned a SURF points object, containing information about SURF features detected in a 2-D grayscale. The work is carried out on every image.

After extracting the important and unique points of the image, features are extracted, descriptors are derived from the pixels surrounding the point of interest. They are required to describe and match features defined by a single point location for all image dimensions. When SURF is used to extract descriptors, the orientation property of returned valid_points is set to the orientation of extracted features in radians. This is useful for visualizing the descriptor orientation.

Also, features are extracted by using the SVD transformation. SVD converts any matrix to three matrices (U, S, and V), these three matrices are saved as a vector of features.

Features from SURF and SVD are added to create a new matrix. The new matrix will be useful for Matching and Blending. Image height will be resized according to the empty panorama dimension. The first image is projected on the empty panorama.

The same steps will be repeated for the next image (and each image in the set of images). The matching process at this step will be achieved by the features vector of the current image with the features vector of the previous image. The purpose of this step is to compare the robust features between images and finding a match between the features of the input images. RANSAC algorithm will be used to removes the incorrect points and makes the correct points as the solder points to get a good panoramic image.

The final step in image stitching is the geometric estimation, where the geometric transformation between each matched pair of features is calculated, and estimating the output from the transformation. This step is applied to align all images. The image is inserted in the panorama after resizing its height. Figure 11 shows the block diagram of the suggested algorithm.

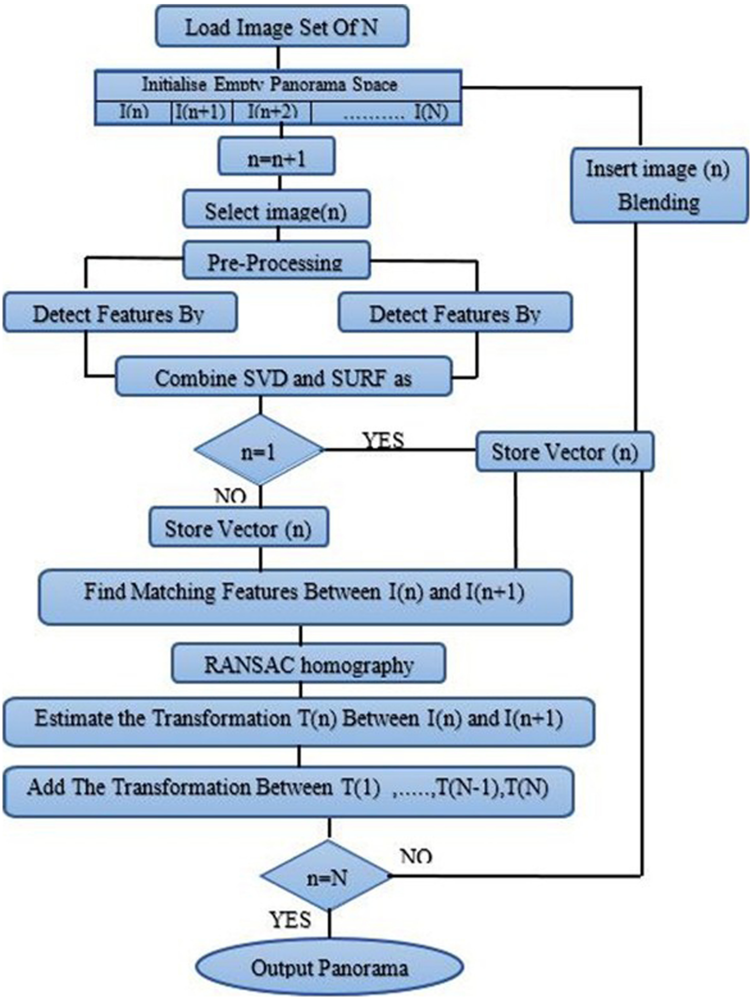

Fig. 11. Proposed algorithm block diagram.

8 Results and Discussion

Many tested are implemented to prove the strength of the proposed algorithm as follow:

8.1 Stitching Images Under Normal Conditions

In this test, images with overlapping regions and without noise or illumination variation are suggested to be used in this test to make a panorama. The number of images used in this test was two images. The result of the stitching process is shown in Fig. 12. Resulted image from this test shows a high-quality panoramic image.

Where images in Fig. 12 (a) are the images acquired from different points, and Fig (b) refers to features extraction and point detection, Fig (c) refers to matching with points, Fig (d) the panoramic images obtained from the suggested method, and Fig (e) The final panorama image after cutting the extreme areas.

The resulting panorama in Fig. 12 (e) and most of the previous algorithms face the problem of appearing a line separating the images that are stitching (bounding in red lines for indication). This problem is due to the variation of lighting of the images to be stitching.

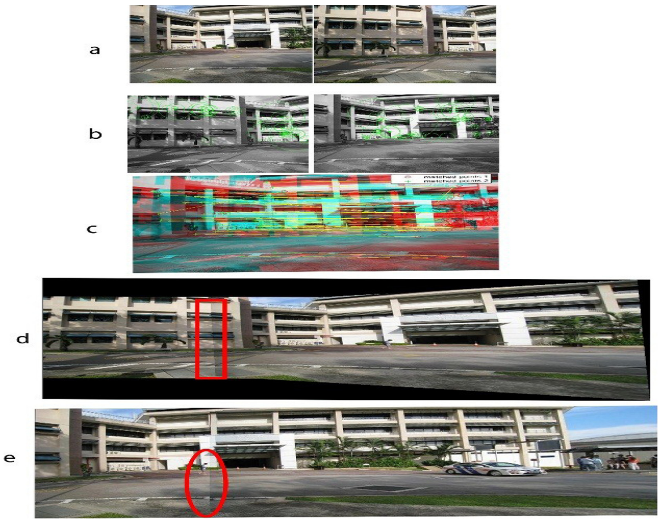

Fig. 12. Results under normal conditions

To solve the problem of appearing lines between stitching images, contrast enhancement will be implemented on the images before the stitching processes. The result of this work show in Fig. 13. The resulting panorama is smooth with high quality.

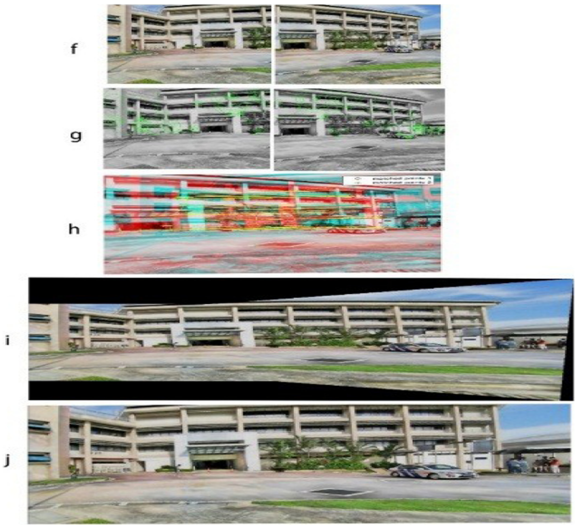

Fig. 13. Results Enhancement under normal conditions

8.2 Stitching Many Images with Normal Conditions

The suggested algorithm was tested by stitching eleven images with a resolution of 1280 × 1920 pixels without noise or illumination variation. The result of the stitching process is shown in Fig. 14. The resulting image from this test shows a high-quality panoramic image. Panoramic image quality measured by NIQE was 3.34; this value is represented good image quality. The rotation of the camera in this test was 5°.

Fig. 14. The top row of images is the input images from a synthetic dataset, while the bottom image is the panorama stitching with alignment in the left image, and the panorama stitching with cropping of alignment in the right image.

8.3 Stitching Images with Poor Illumination

The suggested algorithm is also tested by stitching eleven images with a resolution of 5740 × 3780 pixels, without noise but with poor lighting. The result of the stitching process is shown in Fig. 15. The resulting image from this test shows a high-quality panoramic image. The image quality was measured by several measures, including NIQE, and the result was 3.24; this result indicates good image quality. Also, the image perception measured by BRISQUE, the result was 40.2. This result is also good because the stitching was under poor lighting. The rotation of the camera in this test was 15°.

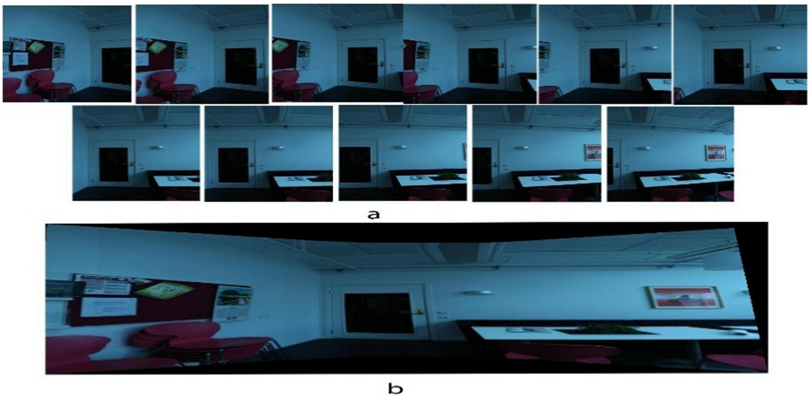

Fig. 15. Show the eleven-input image at the top with the resulted panorama image in the bottom

8.4 Stitching Images with Various Illumination

The strength of the proposed stitching algorithm is tested by stitching three images with a resolution of 2325 × 3150 pixels, without noise, but with various illumination. The result of the stitching process is shown in Fig. 16. The resulting image from this test visually shows a high-quality panoramic image. The image quality was measured by the BRISQUE tool, and the result was 35.25, and this result is good because there are no problems in the image in terms of noise and lighting after the stitching. The rotation of the camera in this test was 20°.

Fig. 16. (a) Images under natural conditions from different angles with stitching output for panorama., (b) Images & panorama after processing using histogram Equalization

8.5 Stitching Images with Noise

The strength of the proposed stitching algorithm is tested by stitching three images with a resolution of 512 × 512 pixels, with the noise of Gaussian type, and with various illumination. The result of the stitching process is shown in Fig. 17. The resulting image from this test visually shows a high-quality panoramic image. The image quality was measured by using the PIQUE tool, and the result was 24.003, and this result is good and acceptable image quality.

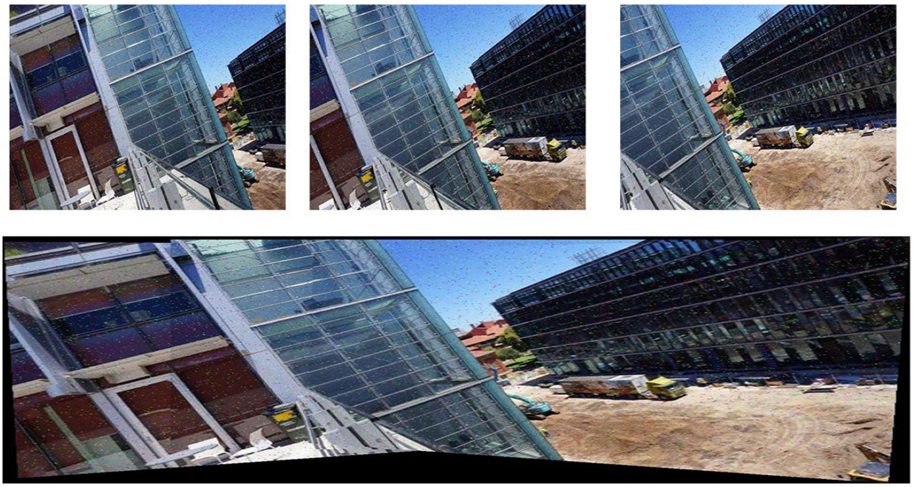

Fig. 17. Show the three-input image with noise at the top with the resulted panorama image in the bottom

8.6 Stitching Images with Geometrical Images

The strength of the proposed stitching algorithm is tested by stitching two images with a resolution of 516 × 505 pixels, with the geometrical images, the result of the stitching process is shown in Fig. 18. The resulting image from this test visually shows a high-quality panoramic image. Panoramic image quality measured by NIQE was 5.34; this value is represented good image quality. The overlap of the image in this test was 5%

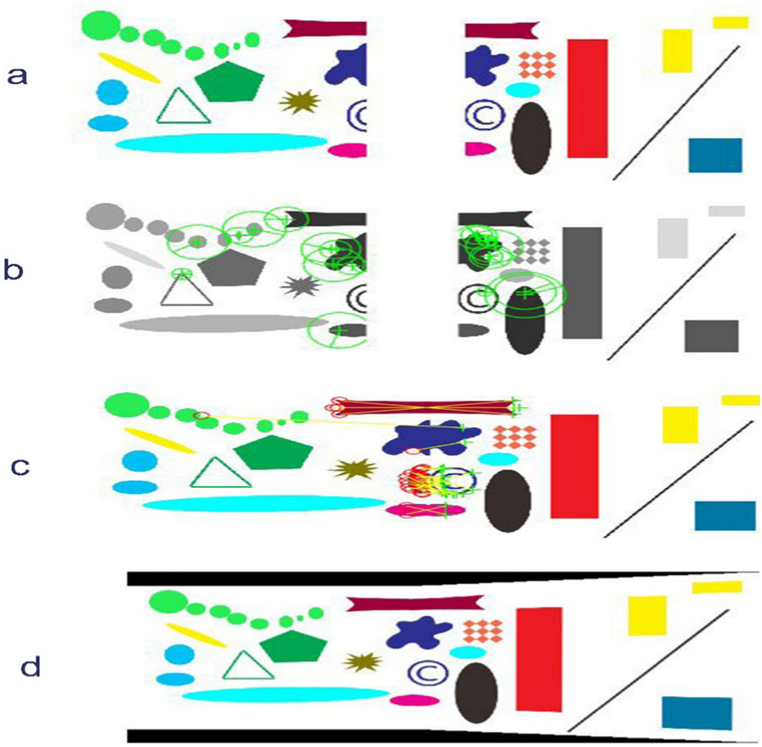

Fig. 18. Results panorama geometrical images

8.7 Comparing the Results

Results of the proposed algorithm were compared visually with other similar works, as shown in Fig. 19. While Table 1 shows the comparison of different methods according to the quality metrics. The results of stitching the panoramic image were uneven.

Fig. 19. Results for a collection of techniques used to stitch the images, such as SURF_SVD, APAP and BRSH, CPW for different image dimensions, and different amounts of exposure for several scenes

The input images in Fig. 19 are two images of different dimensions for several scenes.

The algorithms APAP, CPW, BRSH, and the proposed algorithm SURF_SVD used the images in Fig. 19 to create a panorama image and comparing the stitching performance of these algorithms. Each of these algorithms has its stitching mechanism.

Quality assessment tools used to measure the performance of these stitching algorithms results are listed in Table 1. The result shows better performance comparing with the BRSA and CPW and good performance comparing with APAP. Running time or the proposed algorithm is very good comparing with other methods.

Table 1. Measuring image quality after stitching process.

Measures	SVD-SURF	APAP	BRSA	CPW
PIQUE	49.88	43.18	43.38	185.3
NIQE	2.55	1.92	2.64	16.55
BRISQUE	41.26	29.64	47.65	28
NCC	0.86	0.94	0.875	0.82
SIMM	0.43	0.40	0.56	0.39

Figure 20 illustrates the result obtained by applying the proposed method to the apartment dataset [24] with different algorithms, respectively. Each figure is divided into 12 sub-figures denoted by the letters (a) to (l). Each figure's first row (a,c) displays the findings produced using the SIFT technique. Similarly, the second, third, and fourth lines depict the outcomes obtained using the algorithms (SURF-SVD, AKAZE, ORB). Each row contains two columns: the first column contains the initial matching points, while the second column contains the correct matching points after the false match are deleted. The third column shows an image stitched together using a specific algorithm (SIFT, SURF-SVD, AKAZE, ORB).

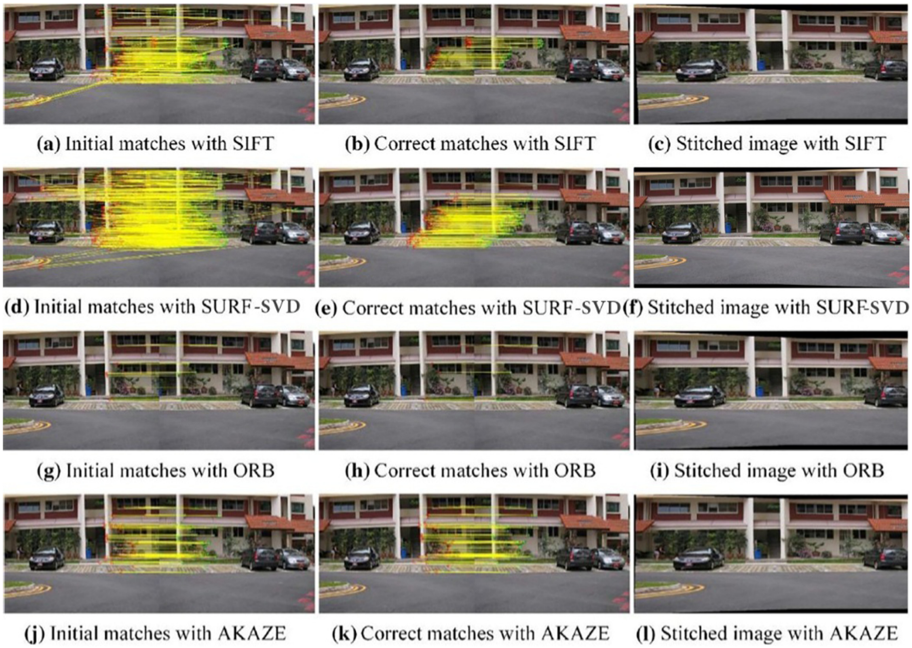

Fig. 20. Results of image stitching and feature matching using the SURF-SVD, ORB, SIFT, and AKAZE algorithms on an apartment dataset

Quality assessment to measure the performance of these stitching algorithms results are listed in Table 2. The result shows better performance comparing with the SIFT and ORB and good performance comparing with AKAZE. Running time or the proposed algorithm is very good comparing with other methods.

Table 2. Comparison of stitched image quality and time required.

Apartment dataset	PSNR	FSIM	VSI	SSIM	TIME
SIFT	15.925	0.6600	0.8724	0.5046	2.1006
ORB	15.403	0.641	0.8640	0.4978	0.1704
SURF-SVD	30.821	0.6676	0.8986	0.5284	1.9271
AKAZE	15.758	0.6733	0.8786	0.5194	1.9759

9 Conclusion

A feature-based image stitching algorithm by SURF_SVD was presented in this paper. Up to our knowledge, this is the first time using the SVD in stitching. The experiment tests prove the robustness and strength of the proposed algorithm against the noise, different resolutions, overlapping size of stitched images, camera focal length, and camera movement. It has a good ability to stitching images in an uncontrol environment. It solves many stitching problems, such as illumination variation and image scaling. It removes the effect of different image illumination and contrast from the resulted panorama. The current algorithm has the ability to stitching many images (more than fifteen images) efficiently. The proposed algorithm is fast and gives a visually very pleasant panorama image. The algorithm compared with other algorithms, and the results were good and promised.

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