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Review Article

A Comparative Study on Different Image Stitching Techniques

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Abstract - *Image stitching/mosaicking is a hot research area in computer vision. Image stitching is a method for combining several images of the same scene into a single composite image. The three most significant components of image stitching are calibration, registration, and blending. In this article, we analyzed different image stitching techniques. Based on image registration methods, image stitching is broadly classified into Spatial domain-based stitching and Frequency domain-based stitching. Direct method and feature-based methods are two types of Spatial domain-based stitching. In the indirect method, the pixel-wise similarity between images is measured to identify the overlapping area, whereas the feature-based method uses image features for similarity measurement. From the study, we identified open challenges and future directions. Therefore, we aim to propose a novel image stitching technique in different domains to rectify those anomalies, such as transformation invariance in both spatial and frequency domains.*

Keywords - *Image stitching, registration, blending, direct Method, feature-based Method.*

1. Introduction

Image stitching is when more than one image of the same scene is merged to produce a new composite image with a wider view. Image stitching has a broad range of applications such as panoramic image production, satellite image synthesis, image mosaicking, computer vision for topographic mapping, recovery of original data from ripped data, motion detection and tracking, forensics and investigation science for toned paper reconstruction, image mapping, resolution enhancement, medical imaging etc. Different authors propose image stitching methods for these applications [1]–[8]. Our study focuses on image stitching for creating panoramic images, which is nowadays used in the Photographic field. Image stitching constitutes three steps: image registration, calibration, and blending [9].

The exact overlap between the input images must be established to stitch multiple images of the same scene. The most critical step in image stitching is registration. It is the method of integrating a series of photographs with overlapping regions taken from various angles into a single frame. Without identifying the exact overlap and applying appropriate transformations, one cannot produce a perfect stitched image. Based on the image registration algorithms, image stitching techniques are divided into two groups based on the registration process used: 'direct technique' and 'feature-based technique'. In the direct technique, the overlapping region between two input images is identified by comparing the pixel values of the images.

In contrast, feature points in the images are identified in feature-based image stitching. These detected feature points/key points/ interest points/ salient points are matched with each other to find the similar one. Based on the locations of the matching feature points, appropriate geometric transformations are applied to align the source images to form a composite one. The sequence of images can be captured by the same device or a different device. We reviewed different image stitching approaches based on registration and blending methods. Irani M and Anandan P reviewed direct image registration methods in [10]. It is evident that though there are advanced registration and blending methods, there is a wide scope for improving the stitching methods by incorporating different future scopes of image stitching. The main challenges of image stitching are parallax errors, moving objects, illumination variation, varying lighting conditions. While taking photos using handheld cameras, uncertainty occurs while moving the cameras to different positions.

The remaining sections of the paper are organized as follows: The general methods of image stitching are discussed in Section II. Section III discusses the classification of different image stitching techniques. In Section IV, different steps involved in feature-based image stitching are discussed. In section V, we reviewed related literature on image stitching, and the identified research gap is explained in this section. The performance analysis of various image stitching techniques is discussed in section VI. Section VII gives a summary of image stitching techniques.

In Section VIII, we bring the paper to a conclusion with the future directions in the stitching area. Finally, section IX discusses the challenges, open issues, and future directions of image stitching.

2. General Steps in Image Stitching

Image/Photo stitching/mosaicking is done through three steps: calibration, registration, and blending [12]. Fig. 1. depicts the steps involved in image stitching. The initial step in any image stitching procedure is image acquisition. The action of retrieving an image from several sources can be broadly defined as image acquisition [13]. Different types of sensors can be used for image capturing. For panoramic image stitching, images can be acquired by moving the camera in different sequential directions. Optical defects are reduced through calibration. Registration is the process of aligning multiple images using appropriate transformation. Image blending is used for removing the visible seam across the boundary area between the input images.

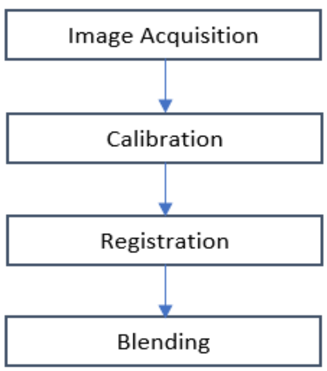

Fig. 1 Steps of Image stitching

2.1 Calibration

Calibration minimizes optical defects such as optical distortions and perspective distortions. Calibration also aims to reduce exposure differences between input images, camera response and chromatic aberrations [13]. It is also used for retrieving the intrinsic and extrinsic camera parameters. Zhengyou Zhang proposed a technique for camera calibration in 2000 [14]. This approach starts with a closed-form solution and then refines it nonlinearly using the maximum likelihood criterion. The proposed technique was tested using computer simulation and real data and achieved positive results. The researchers also compared their methods to traditional procedures requiring costly equipment like orthogonal planes. The proposed camera calibration method is a versatile tool. An effective calibration approach was introduced by Junchao Zhu in 2015 [15] to overcome the problem of minor mistakes caused by encapsulating structure installation and production. Furthermore, the inaccuracies are difficult to quantify, resulting in the optical axis of lenses not being parallel. The final experimental findings show that this strategy is practical.

2.2 Registration

Registration is the most critical step in the image stitching process. The process of aligning different images taken from single or multiple viewpoints by different sensors and at different times is known as image registration [17]. Image registration determines the geometric correspondences between two images to calculate the best transformations to match the input images. Registration is generally of two types, direct Method and feature-based Method. A detailed review of registration for image stitching is given in the next sections of this paper. Lots of methods are there in these two types of image registration. Different authors also do different reviews in the articles. A comparison of three common feature detectors such as Scale Invariant Feature Transform (SIFT), Principal Component Analysis SIFT (PCA-SIFT), and Speeded Up Robust Features (SURF) is done in [17] by Luo Juan and Oubong Gwen. A survey of image registration techniques is conducted by Lisa Gottesfeld Brown in [18]. Joaquim Salvi et al. reviewed a different range of image registration methods in 2007. The accuracy of different registration algorithms is also evaluated [19].

2.3 Image Blending

Images are put in the correct position in the final frame after registration. There is a possibility that geometric and photometric misalignments will occur during stitching. This irregularity would result in discontinuities and the apparent seam between the stitched image around the boundary. The image blending algorithm aims to eliminate visible seams across the stitch. For image blending, there are different types, such as alpha blending and the Gaussian Pyramid [20]. In 2010, Yingen Xiong and Kari Pulli proposed a gradient-domain image blending technique for mobile devices [21]. To build a composite image, graph cut optimization is utilized to discover ideal seams in overlapping portions of the source images. The application of graph-cut optimization over the source images ensures that ideal seams are found, which is one of the advantages of the suggested method. The resulting composite image represents the optimal global solution. Sequential image blending and global image blending are two methods for implementing the method. Sequential image blending allows for the most efficient memory use during the whole blending process. The use of global image blending ensures that a globally optimal solution is achieved. A mask-based image blending was also proposed by Yingen Xiong and Kari Pulli in 2010 [22, p.]. The work is aimed at implementing blending in mobile panoramas. A single-channel mask is constructed and initialized with dispersed values for each source image in this method. The mask's values are weighting coefficients for combining photos to create a panoramic image. It has a minimal computational and memory cost compared to other difficult methodologies like gradient-domain image blending. It may also be used to stitch 2D panoramas and has a superior blending quality.

The method is used to create panoramic photos for preview in a mobile panorama system.

3. Classification of Image Stitching

Image stitching techniques are divided into two categories based on the registration algorithm used for stitching. Spatial domain-based and frequency domain-based are the two main categories [23]. Area-based (Direct method/pixel-based) image-stitching and 'feature-based' image stitching are two spatial domain-based image stitching types. Fig.2. shows the registration-based classification of image stitching. The indirect method, similarity measurement techniques such as the Sum of absolute difference, Sum of squared difference, correlation methods and mutual information can be used for finding the overlapping area in input images. The feature-based method uses any of the feature detectors such as Harris corner detector, Forstner corner detector, Smallest Univalued Segment Assimilating Nucleus (SUSAN), Feature from Accelerated Segment Test (FAST), SIFT, SURF and Oriented FAST and Rotated BRIEF (ORB). The area-based method finds the pixel-wise similarities between images. In contrast, the feature-based method extracts the salient key points/feature points and matches these features for finding the overlap between the input images.

3.1 Spatial Domain-based Image Stitching

This category of image stitching uses pixel intensity properties to perform image registration. In the spatial domain, image stitching may be area-based or feature-based. Pixel-based or direct image stitching is another name for area-based stitching/mosaicking. The matching operation is carried out by comparing each pixel between two images rather than the feature-to-feature matching.

3.1.1 Direct Method

To find the overlapping region between the images, the direct method/area-based image stitching method compares all pixel intensities of the images. Different similarity measurement techniques such as Sum of squared difference, Sum of absolute difference, Correlation methods, Mutual Information method etc. [10] can be used for obtaining the matching area.

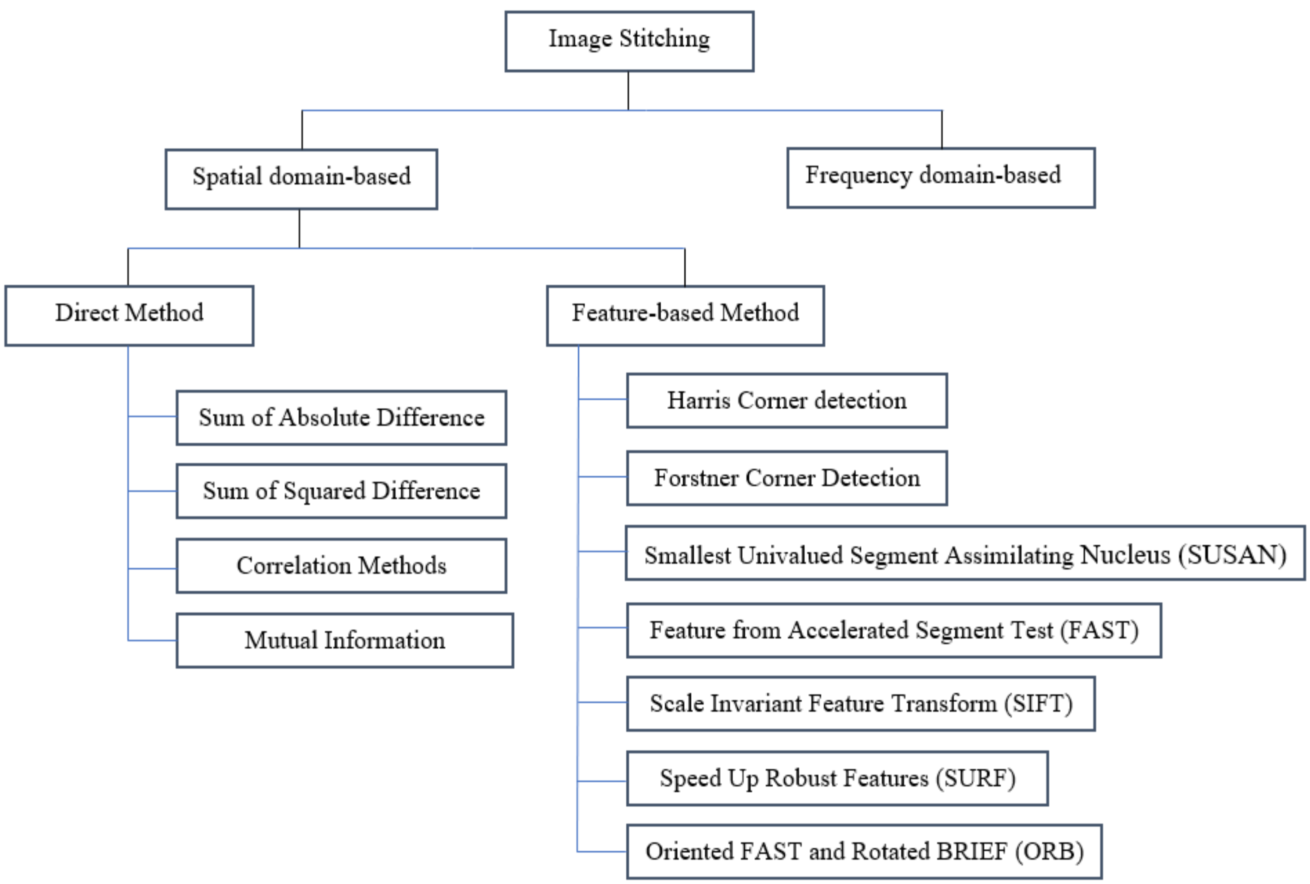

Fig. 2 Classification of image stitching techniques

Sum of Absolute Difference

Sum of Absolute Difference (SAD) can be applied in image stitching applications where motion estimation is necessary [10]. SAD between two images I0 and I1 can be calculated as,

$$SAD(u)=\sum_i|I_0(x_i+u)-(I_1(x_i)| \quad (1)$$

Sum of Squared Difference

Transferring one image relative to the other is one of the simplest ways to obtain the overlap area between two images. The overlapping area can be determined by searching for the minimum Sum of Squared Difference (SSD) between two images [10]. Assume that $I_1(x)$ and $I_2(x)$ are two images that are to be matched with each other; SSD can be calculated as given in Eq. (2).

$$SSD(u)=\sum_i[I_2(x_i+u)-(I_1(x_i)]^2 \quad (2)$$

3.1.2 Correlation Methods

Correlation can be done to discover the intensity difference between two images. In other words, optimize the aligned cross-correlation (product) of the two images. It is a technique for patch-wise matching. As given in Eq. (3), correlation can be performed.

$$C(m,n) = \sum_x \sum_y I_0(x, y)\, I_1(x-m, y-n) \quad (3)$$

C (m, n) is the correlation ratio between the template image and the target image, I_1 (x, y) is the template image/patch, I_2(x, y) is the target image and (m, n) is the displacement parameter.

If brightness variation is present in two images of the same scene, maximum correlation lies in that bright patch. This will not provide a perfect match after performing a cross-correlation operation. Normalized Cross-correlation (NCC) can be used to solve this problem [10]. Normalized Cross-correlation can be performed as given in Eq. (4),

$$NCC(u)=\frac{\sum_i\,[I_0\,(x_i)-\bar{I_0}][I_1\,(x_i+u)-\bar{I_1}]}{\sqrt{\sum_i[I_0\,(x_i)-\bar{I_0}]^2\;[I_1\,(x_i+u)-\bar{I_1}]^2}} \quad (4)$$

$$\bar{I_0}=\frac{1}{N}\sum_i I_0(x_i) \quad (5)$$

$$\bar{I_1}=\frac{1}{N}\sum_i I_1(x_i+u) \quad (6)$$

The mean images of the associated patches are $\bar{I_0}$ and $\bar{I_1}$, respectively, and N denotes the number of pixels in the patch. The NCC value will always fall within the range [-1,1]. A template matching algorithm based on Normalized Cross-Correlation (NCC) was proposed by Shou-Der Wei and Shang-Hong Lai in 2008 [24]. The observed limitation of correlation-based image registration is that it is not invariant to scaling and rotation. It fails to align when the images are in different scales and orientations.

3.1.3 Mutual Information Method

Image similarity can be determined by calculating the Mutual Information (MI) between images. MI-based image registration calculates the mutual probability of the intensity values of corresponding pixels in the two images. Consider two images, I_1 and I_2. Mutual Information between I_1 and I_2 is calculated as follows,

$$MI(I_1,\, I_2) = H(I_2) - H(I_2|I_1) \quad (7)$$

$H(I_2)$ denotes the Shannon entropy of image B. The conditional entropy $H(I_2|I_1)$ is dependent on the conditional probability $P(I_2|I_1)$ [11]. P. Viola and W.M Wells proposed a method for image alignment by formulating MI between two images.

The main limitation of MI-based image registration is the performance of the registration will decrease if the images have a low resolution or when the overlapping region is low [24]. Because they calculate the contribution of each pixel in the image, the direct technique has the benefit of using optimal information for matching. Direct approaches have the largest drawback of having a narrow range of convergence.

3.1.4 Feature-Based Method

In this method, feature points in the images, such as corners, blobs, are extracted, and these extracted feature points descriptors are compared with each other to find the overlap area. The correspondences between images and homography can be measured from the locations of the extracted matching feature points. Images are first warped and then aligned into a final frame using homography matrices [25]. More details about feature-based image stitching are explained in Section 4.

3.2 Frequency Domain-Based Image Stitching

Frequency domain image stitching is based on Fourier Transform (FT). FT is the correlation of two images computed as the product of FT coefficients of one image and the complex conjugate of the other [26]. Phase correlation-based image registration is based on the Fourier Transform. In this method, the overlapping area between two input images is identified by performing the elementwise product of the Fourier transform of one input image with the complex conjugate of the Fourier transform of the second input image [26]. The cross-correlation based image stitching can handle either horizontally displaced images or vertical displaced images simultaneously for obtaining the overlapping region. This limitation can be overcome by using phase- correlation-based registration. The phase-correlation based image stitching algorithms can stitch images with horizontal and vertical shifts simultaneously. Several image registration methods are proposed based on phase correlation [27],[26]. Fourier-based methods are often used to speed up image registration computations.

4. Steps in Feature-Based Method

The key steps in feature-based image stitching are image acquisition, feature detection and matching, homography estimation, image warping, and image blending[28]. Figure 3 depicts the various phases involved in feature-based image stitching. Image acquisition is the first step. Two or more images having overlapping areas are used as the input image. These images can be taken from a single sensor or multiple sensors simultaneously or at different times. The next step is detecting the features in the input images. Any feature detectors such as SIFT, SURF etc., can be used for this purpose. The detected features are compared to find the matching pairs to find similar regions in the input. Homography is estimated from the location of the matching features in the input images. RANSAC (Random Sample Consensus) is a widely used outlier detection. It is used for removing the mismatching feature pairs to increase the accuracy of the alignment of images. Image warping is the next step that applies appropriate transformations and modifications to make a perfect composite image. Image blending is the final step of image stitching. If there is any visible seam across the stitched input images due to intensity variations in the images, the blending technique removes the visible seam. There are different types of blending that can be used in stitching. It is explained in detail in section 4.5. Finally, the final output composite image without seams can be produced [30].

4.1 Image Acquisition

For any stitching application, multiple input images are fed to the system. Input images are collected by any acquisition method. The first step in the image stitching process is image acquisition. It is the method of collecting an image from a variety of sources. Images for panoramic photography can be captured by moving a camera from sequential directions. The movement of the camera should be parallel to the scene. Another way of capturing images is rotating a camera around its vertical axis or using a handheld camera [13].

4.2 Feature Detection and Feature Matching

In feature-based image stitching, feature detection and matching are the two main stages. The feature-based image stitching method can improve the overall speed of the image registration process. The whole area of images need not be processed for finding the overlapping region. Only the detected feature points are used for finding the matching area between images. Features in an image can be corners, lines, edges, blobs etc. Most widely used feature detectors are Harris corner detector [30], Smallest Univalued Segment Assimilating Nucleus (SUSAN) [31], Forstner corner detector [32], SIFT [33] and its variants such as PCA SIFT [17], Colour SIFT [17], Affine SIFT [34], Octave SIFT [17], SURF [35], ORB [36] etc. To obtain the matching features, the descriptors of the detected features are created first.

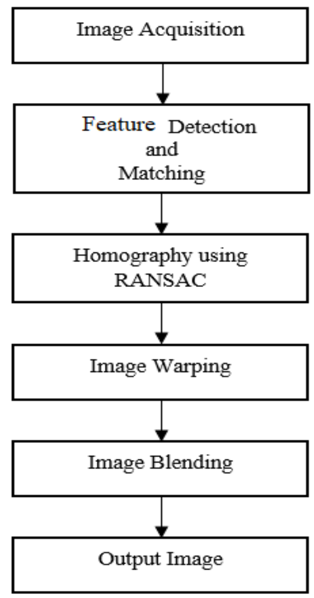

Fig. 3 Image stitching based on feature detection

4.2.1 Harris Corner Detector

Chris Harris and Mike Stephens proposed the Harris corner detector in 1988 [30], an auto-correlation-based corner and edge detector. It is a method inspired by the Moravec corner detector. Harris corner detector considers the differential of the corner score. Suppose 'I' is the image in which corners are detected. Consider an image denoted by (x, y) and translated by a distance (m, n). The SSD between the two patches is calculated as follows:

$$\text{SSD}(m, n) = \sum_x \sum_y (x, y)\,(I(x + m, y + n) - I(x, y))^2 \qquad (8)$$

By using tailor expansion and partial derivative, (8) can be written as follows:

$$S(x,y) \approx (x,y) A \begin{pmatrix} x \\ y \end{pmatrix} \qquad (9)$$

$$A = \sum_{xy} w(x,y) \begin{bmatrix} I_m^2 & I_m I_n \\ I_m I_n & I_n^2 \end{bmatrix} \qquad (10)$$

$$= \begin{bmatrix} < I_m^2 > & < I_m I_n > \\ < I_m I_n > & < I_n^2 > \end{bmatrix}$$

A is the Harris matrix. The angular bracket indicates the averaging operation. A big change of S in all vector directions characterizes a corner (m, n) [17].

Smallest Univalued Segment Assimilating Nucleus (SUSAN)

Stephen M. Smith and J. Michael Brady proposed lines, corner and edge detector in 1973, known as SUSAN [18]. Feature detection is based on the minimization of the local image region. The SUSAN principle is based on the idea that each image point has an area of similar brightness. A window is placed over the pixel to be checked in the SUSAN algorithm. The brightness of the nucleus is compared to each pixel in the mask.

Forstner Corner Detector

Forstner corner detector was proposed by W. Forstner and E. Gulch in 1987 [34]. The corner extraction consists of two steps; Window selection and feature location. If we want to pinpoint the exact position with subpixel precision, we can use this detector. Corner detection using the Forstner method is depicted in Fig. 4. The Forstner algorithm is a least-square solution that finds the point in a given window nearest to all of the tangent lines of the corner [37]. Tangent lines intersect at a single point in an ideal corner.

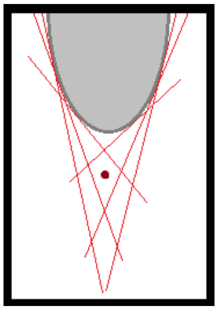

Fig. 4 Corner detection using Forstner Method

Scale Invariant Feature Transform (SIFT)

A distinctive key-point detector and descriptor called SIFT were proposed by David G. Lowe in 1999 [33][34]. It is a popular image matching technique focused on local image features. The steps involved in SIFT are the construction of scale-space, discovering extrema of scale-space, key-point localization, orientation assignment and creating key-point descriptors. Initially, scale-space is constructed by repeated convolution of the image with a Gaussian filter while adjusting the Scale and grouping the result into octaves, as shown in the equation below.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \tag{11}$$

Equation (10) demonstrates how to calculate the difference between adjacent Gaussian (DoG) images.

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \tag{12}$$

Local extrema of DoG images around the Scale are marked as possible candidate key points. Fig. 5. shows scale-space design, DoG construction, and scale-space extrema detection. Extrema detection in DoG scale space is depicted in Fig. 6. With correct key-point localization, low contrast keypoints are discarded. The key-point orientation is determined by the local image gradient directions [33].

RANSAC algorithm is used for outlier detection and to compute the transformation parameter [1]. Images are warped and aligned to create the final composite image using the transformation parameter obtained. The SIFT algorithm is good for stitching high-resolution images with rotation, Scale, and affine motion changes. However, one drawback is the lengthy processing time.

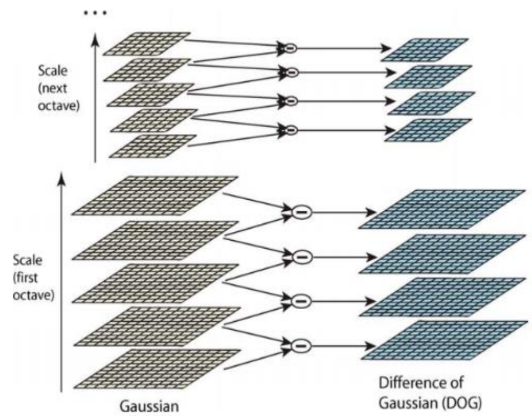

Fig. 5 Scale-space creation and Difference of Gaussian (DoG) calculation, adapted from [33]

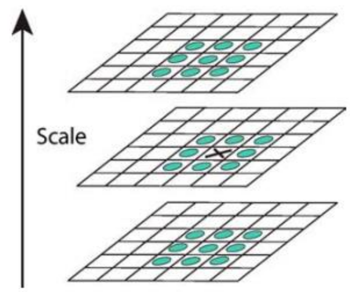

Fig. 6 Extrema detection in DoG scale space, adapted from [33]

Feature from Accelerated Segment Test (FAST)

Rosten E. and Drummond T. introduced FAST, a fast corner and interest point detection algorithm, in 2006 [19]. They used a Machine Learning approach to hasten the corner detection process. The FAST detector compares pixels on a circle with a fixed radius centred on a point to detect interest points. The FAST algorithm considers a 16-pixel circle around corner candidate p, as shown in Fig. 7.

The main advantages of FAST are, it is faster than other Harris corner detection algorithms and has a high level of repeatability. However, it is not resistant to high noise levels [37].

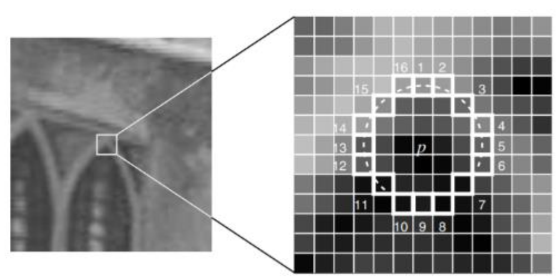

Fig. 7 The corner detection by using the FAST algorithm, adapted from [37]

Speeded Up Robust Features (SURF)

Herbert Bay et al. introduced SURF in 2006 [35]. SURF is a faster algorithm than SIFT, and it is said to be more resistant to image transformations. The first step in the SURF algorithm is to select key points such as blobs, corners and T-junctions in the image [35]. A distinctive feature vector is used to represent the neighbourhood of the key point. The descriptor should be distinct and resistant to noise, detection errors, and geometric distortions. Key points are compared by matching the feature vectors. The SURF algorithm uses integral images and the Sum of 2D Haar wavelet responses. It employs an integer approximation to the Hessian blob detector's determinant, which is determined using an integral image of the source image. Fast computation, suitability for real-time monitoring, and object recognition are the key advantages of the SURF algorithm. It accelerates the SIFT detection process by ensuring that the detected key points are of high quality. The processing speed of feature vector matching is increased. The Hessian matrix is used in conjunction with descriptors to minimize the dimensionality of the descriptors, resulting in a faster matching process. The limitation of SURF is that poor at handling viewpoints and illumination changes [34].

Oriented FAST and Rotated BRIEF (ORB)

The ORB algorithm is based on the Binary Robust Independent Elementary Features (BRIEF) [23], which is an extremely fast key-point descriptor. The binary-based features are better than vector-based features in terms of computation speed, storage, comparison efficiency. The ORB descriptor uses the well-known FAST key-point detector as its foundation. These methods are effective due to their high efficiency and low cost. ORB provides a fast and accurate orientation component.

4.3 Homography estimation using RANSAC

To produce high accuracy alignment, finding the most suitable feature correspondences is necessary. i.e., outliers among the set of initial feature correspondence should be eliminated. Random Sample Consensus (RANSAC) and Least Median of Squares are two commonly used solutions for outlier detection [38]. The RANSAC algorithm cannot guarantee that suitable results will be returned in all cases, So this algorithm is termed a nondeterministic algorithm. The outlier detection of the RANSAC algorithm is performed iteratively, i.e. it selects four feature point pairs at random; the homography H of the randomly selected feature points are then estimated after that. All the inliers are counted one by one from the homography H, keeping the maximum number of inliers. Finally, the least-squares H estimates are calculated on all inliers [12].

4.4 Image Warping

The method of digitally modifying an image to eliminate distortion during the transformation operation is known as image warping. The term "warping" refers to mapping points to other points without changing the intensity values [39]. It can be used to eliminate optical distortions caused by a camera or a specific viewing angle, register an image with a map or prototype, or align two or more images in various image analysis problems. The chosen warp is a balance between a smooth distortion and a good match. Smoothness can be achieved by giving the warp a parametric shape or constraining it with differential equations [39]. Points to be aligned, local similarity measures between images, or edge coincidence may all be used to specify matching. The final operation is to blend the intensities of the pixels in the stitching boundaries to eliminate seams [10].

4.5 Blending

Image blending is another key step of image stitching. It is used to remove any apparent seams that may appear in the final composite image due to misalignments, camera exposure differences, scene lighting variations, or the presence of moving objects between frames and lack of proper geometric alignment [40]. If registration is done perfectly and there are no exposure differences in input images, blending is an easy task. There are different types of blending techniques. Transition smoothing and optimum seam finding are the two types of blending techniques [21]. Feathering and alpha blending are other terms for transition smoothing [22]. Feathering, pyramid blending, and gradient-based blending [23] are common blending methods that use transition smoothing.

4.5.1 Feathering

Blending is accomplished via feathering-based blending, which uses an average value for each pixel in the overlapping zone. The simple average technique fails when moving objects are present in the scene. In such cases, the weighted average method is suitable. Feathering based image blending is used in different image stitching methods [41]–[43]. In [43], the authors used weighted average blending. The blended images by simple averaging blending and feathering-based blending are shown in Figure 8.

4.5.2 Pyramid Blending

In pyramid based blending, the input images are converted into band-pass pyramids. Edge duplication is eliminated in image stitching by using pyramid blending. The pyramid blending combines images with multi-exposure based on the idea of multi-resolution blending. This method is fast in computation. However, double contouring and ghosting effects may appear when there is a severe registration problem. In [8], [41], [45]–[47], pyramid blending is used for final seam elimination.

4.5.3 Gradient Domain Blending

Gradient domain blending is another transition smoothing approach. These methods are based on the premise that mosaic image regions can be realistically mosaiced by properly combining the gradient of images [21]. Levin et al. [40] and Xiong [47] did some noteworthy work.

In [48], Gradient-domain Image stitching is proposed (GIST). In this method, the stitching quality in the seam region is measured in the gradient domain. Generally, the gradient domain-based blending gives more good results than feathering and pyramid blending, but the alignment of source images must be perfect for obtaining good results.

4.5.4 Optimal seam-based Blending

Optimal seam-based blending is another method of image blending [23]. This algorithm searches for the optimal seam in the joining line between the registered images to eliminate the visible seam. The ghost effects in the image can be efficiently eliminated using a blending method based on appropriate seam selection. In general, the best stitching seam algorithm is to identify an optimal path in the overlapping area of two photos to avoid locations where the two images have major textural variations. Marie-Lise et al. [49] use dynamic programming to identify the best seam based on the search criteria. By studying the overlapping region of two photos, the optimal seam blending approach aims to discover the best spot for a seam line. The works in the article [49]–[53] are some of the ways that made advantages of optimal seam-based blending.

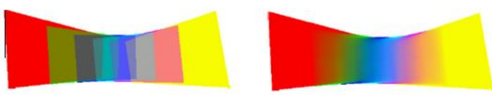

Fig. 8 (a) Simple average blending (b) feathering-based blending (adapted from[23]**)**

5. Literature Review

In 2013, V. S. Bind et al. proposed an image mosaicking technique focused on features based image fusion. [54]. The proposed technique consists of two stitching algorithms such as SIFT and SURF. The proposed method combines both methods by using the optimum image fusion algorithm. The fusion operation is carried out by using Haar Discrete Wavelet Transform. It is evident from the verification of results obtained using MI, NAE, and other methods that the proposed image stitching outperforms SIFT and SURF algorithms.

Yang F et al. in 2013 proposed a microscopic image stitching method based on the feature extraction approach [7]. Features are extracted using an improved Speeded Up Robust Feature extraction algorithm. The histogram equalization (HE) Method was adopted for pre-processing the image to enhance the image contrast. Through histogram equalization, the number of feature points extracted increased. The phase correlation method identifies the overlapping region of the pre-processed images. The improved SURF algorithm was applied to this identified overlapping zone to extract the feature points. Images are aligned to the common frame by applying appropriate transformations. Finally blending algorithm is used for making the final image seamless. Animal microscopic images of male adult musculus were used for experiments. 40 groups of microscopic images, each 768 ×576 pixels, are used as input images. The limitation of the original SURF was addressed in this paper. While extracting feature points in a microscopic image using SURF, it is not robust to large viewpoint changes. The authors solve this limitation by applying affine transformation in advance to stimulate the viewpoint changes of the image.

While converting RGB image to grayscale image for making it suitable for SURF feature extraction, some of the information may be lost. This problem is solved in the proposed method by pre-processing the grayscale input image using by Histogram Equalization (HE) method. HE Method enhances the contrast of the grayscale image. After that, phase correlation is used for identifying the overlapping regions in contrast-enhanced images. Improved SURF detects the feature points in the identified overlapping regions of the input images. Euclidean distance between detected feature points is calculated for obtaining the matching feature points in the input images. A fusion algorithm based on the weighted average method is used for blending the boundary pixels of two images. In this article, the proposed method is compared with the original SURF algorithm for analyzing the performance. For comparison standard database of Mikolajczyk [7] is used.

The number of feature points detected without HE is 203, and in the second input, it is 141. At the same time, the number of feature points detected in the input images with the HE algorithm is 492 and 376, respectively. The number of matching feature points without HE is 111, while with the HE algorithm, it is 247. The performance is also compared with the commonly used stitching software Autostitch. Autostitch uses Scale Invariant Feature Transform (SIFT) for feature detection. It is partially invariant to zoom, rotation, illumination difference, viewpoint changes, whereas the proposed method is fully invariant, i.e., robust to the variations mentioned above. Autostitch can handle only JPEG images, whereas the proposed method can also handle any type of image format. The identified limitation of this proposed method is that it cannot successfully register distorted input images.

Shaikh T S and Patankar A B 2015 [55] proposed an approach that uses a combination of three feature detection algorithms, namely SIFT, SURF, MSER (Maximally Stable Extremal Region), for creating panoramic images [55]. The advantages of these feature detection algorithms are utilized for improving the quality of the final stitched images. In the feature detection stage of the proposed method, feature points are detected by using SURF, MSER, and SIFT. A combined dataset of these feature points is created later. The basic part of the algorithm includes; feature extraction, feature matching, image transformation and image blending. SIFT, SURF and MSER feature points are detected, and their feature descriptors are calculated initially. FLANN (Fast

Library for Approximate Nearest Neighbour) is used for feature matching. Homography between sets of feature points is determined for image transformation. From the experimental results shown, the proposed image stitching aims to stitch two images of the same scene. It is better than the stitching technique that separately uses the feature mentioned earlier in detection algorithms. But it shows some artefacts while stitching the input image with noise and can stitch 2 input images.

In 2016, Mistry and Patel proposed a feature-based image stitching method based on the Harris corner detector[6]. Chris Harris and Mike Stephens created this operator in 1988.[30]. By comparing the detection rate and repeatability rate, the combined corner and edge detector outperforms the individual detectors but at the cost of a substantial increase in computation time. The Harris corner detector is invariant with rotation, size, variation in illumination and noise in the image. The Harris corner detector works by detecting local signal changes when patches are moved a small amount in different directions using a signal's local autocorrelation function. The RANSAC algorithm is used to approximate mathematical model parameters from a collection of observed data with outliers. The approximate parameters are used to perform image warping and blending.

In 2019, C. Liu et al. proposed a Minimum spanning tree-based Normalized Cross-correlation image stitching technique [57]. It aims to improve the matching speed of traditional image stitching based on normal cross-correlation. For better matching of images, the authors used the minimum spanning tree. For comparison, they used the matrix form of the total incidence matrix method of circle breaking. The basic concept of Normalized cross-correlation is to compare two images based on the similarity of their feature points' neighbourhood pixel grey value. When the maximum similarity between two images occurs, the correlation coefficient is highest. Stitching efficiency is improved by using a normalized cross-correlation based on the minimum spanning tree. The image matching approach using normalized cross-correlation is robust against greyscale and has a modest range of geometric distortion. They developed a new optimization algorithm to address the problem of high computational complexity. It simply requires an 18MN addition operation and 2MN times multiplication. For the experiments, they used two groups of images. For the first group, the total time (in seconds) taken in Traditional NCC, Optimized NCC and proposed minimum spanning tree NCC are 10.47,8.28 and 7.75, respectively. The second group image set time is 14.12, 12, and 11.44, respectively. The suggested algorithm improves the feature points' matching speed. Detection of feature points takes longer than the time taken in conventional Normalized cross-correlation, but the proposed algorithm takes less time to match feature points matching.

In 2019, Byuan Ma et al. proposed the "Very fast sequential micrograph stitching (VFSMS)" algorithm for stitching material images [5]. They used an incremental searching method and GPU acceleration to achieve stitching precision and speed. Datasets consist of three different types of micrographs of various materials, structures, and imaging modalities. According to the experiments, the proposed approach has better performance than other stitching applications such as Photoshop, ImageJ, and Autostitch. VFSMS can save the previous stitching results and continue stitching on the next image when a mismatch occurs. VFSMS consumes less time for stitching than the ImageJ application, which is the common software for material image processing. In addition, the average accuracy of different methods such as Grid stitch, Sequential stitch, Photoshop photo merger, Autostitch and VFSMS is 73%, 55%, 27%, 25% and 100%, respectively. This approach has one limitation; it can stitch only local micrographs in greyscale mode and is not able to fuse micrographs in the RGB Channel. [5] This will result in the loss of colour values in the final micrographs. Another drawback of this method is that the stitching result has a slight distortion, which will affect the quality of the final microscopic image.

In 2020, Zhang Y et al. proposed a hyperspectral image (HSI) stitching algorithm that used robust feature matching and elastic warps [3]. Hyperspectral image contains both spatial and spectral information. Due to a large number of bands, the size of the hyperspectral image is high. Processing all bands of HSI for feature extraction took a large amount of time. So, only one band is fixed as a reference band in the proposed algorithm. There are two stages to the proposed technique. In the first step, one image is fixed as the reference band, and features are extracted using the SIFT method. They created a method for building resilient point correspondences between two points called the multi-scale top K rank preservation algorithm. To create the panorama, they used a strong elastic warp. All remaining images were stitched to the frame in the second stage using the transformation parameters obtained in the first stage. The problem associated with feature detection algorithms for image stitching is the presence of false matches.

The false matches will lead to alignment errors. Zhang Y et al. introduced the mTopKRP algorithm [3]. Features are extracted initially using SIFT, and then the mTopKRP algorithm is applied for removing false matches. Robust elastic warping is used for the warping of source images to the final frame. Different warping, such as Affine transformation-based and Projective transformation-based warping, are used. The problem associated with projective transformation is shape distortion. In the proposed method, the robust elastic warping method is used for image warping to avoid this problem associated with transformation. In the final step, the composite image is made by applying a linear blending algorithm.

Image blending is used for removing the seams in the final stitched image. The feature detection algorithms such as SIFT, SURF and SS-SIFT (Spectral-spatial SIFT) on hyperspectral image (HSI) dataset. Detected matching points in SIFT, SURF, and SS-SIFT are 1176, 80 and 82, respectively. Running time is also compared, and it is 10.12s, 0.849 and 950.311, respectively. They also compared different feature matching algorithms, including RANSAC, LPM (Locality Preserving Matching), VFC (Vector Field Consensus) and the proposed mTopKRP algorithm on remote sensing datasets. The dataset comprises 18 HSIs, each image having a size of 960 ×1057 pixels. On HSI datasets, they compared their findings with ANAP (Adaptive as-natural-as-possible) image stitching, NISwGSP (Natural Image Stitching with Global Similarity Prior), and ELA warping techniques.

In 2021, Yuan Yiting et al. proposed a superpixel process for seamless image stitching [1]. They suggested a new super-pixel-based seam cutting method for UAV (Unmanned Aerial Vehicle) images. They used the ANAP warping method for image registration [1]. They proposed a superpixel seam cutting method that finds an optimal seam on a continuous region. Registration, seam elimination and blending are the three steps in the algorithm. For stitching, two UAV images are used. The AANAP technique was used on the input image to create two warped UAV images. They first introduced superpixel segmentation for seam cutting. It eliminates the pixel-based seam cutting method, such as computational complexity. They also added a cost difference that indicates the similarity of overlapping areas in the input images. The graph cut algorithm was used to solve the problem. The noticeable seams between the two photos are removed using weighted colour blending.

The literature analyzed so far faces the limitation of proper alignment to create the composite image. Direct image stitching can be used only for stitching two or more images that vary either by horizontal translation or by vertical translation operation. At the same time, feature-based image registration is apt for stitching multiple images taken from different viewpoints and orientations. SIFT is Scale and rotation invariant, whereas SURF is invariant to geometrical transformations such as scaling, rotation, and it is faster than SIFT. By analyzing the existing image stitching methods, it is clear that there is a possibility of improving the quality of the stitched image. The stitching accuracy in different performance matrices such as Entropy, Quality index, Standard deviation and Variance can be improved by introducing more advanced algorithms. Most methods are designed to stitch two input images taken by moving the camera sequentially from the left to right direction. An ideal panoramic algorithm should be able to stitch overlapping images taken in all sequential directions, including the right to left, top to bottom, and other sequential movements for capturing the whole scene. So stitching these kinds of sequential images results in a final panoramic image wider field of view.

6. Performance Analysis of Various Image Registration Methods

We analyzed the performance of different image registration methods, such as direct and feature-based methods on camera captured images such as the Unsupervised Deep Image Stitching Dataset (UDIS-D) and Graffiti datasets. The table below shows the total time taken for image stitching using the Cross-correlation and Phase Correlation technique on real-time image data set.

The table shows the time taken by image stitching methods using different direct image registration methods on real-world images, as shown in Fig.9.

Fig. 9 Image stitching using phase correlation

Table 1. Time is taken for image stitching by direct-methods

Method	Time in Seconds
Cross-correlation	58
Phase correlation	32

Table 2 shows the total time taken for stitching by using different detectors. We have considered the Graffiti data set for comparing the performance of Feature detectors. Fig. 10 shows two input images from the Graffiti dataset taken from different viewpoints with affine transformation and the corresponding stitched image using SIFT. The size of input images in the Graffiti dataset is 300×240 pixels. The time taken by different algorithms for stitching is given in Table II. Table II shows that SURF is the fastest one, while SIFT requires the longest time to process among all other feature detectors.

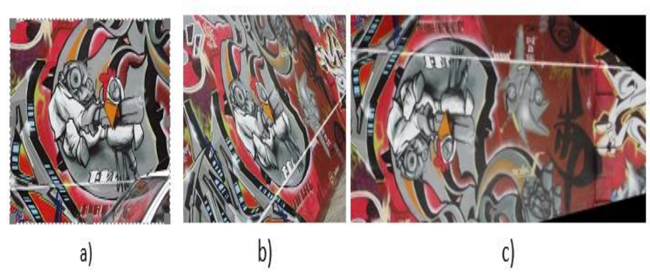

Fig. 10 a) First Input image. b) Second input image is taken from a different viewpoint with affine transformation. c) Stitched image using SIFT

Table 2. Time is taken for stitching using feature-based algorithms

Method	Time is taken for stitching(s)
Harris Corner detector	0.456237
SIFT descriptor and its variants	0.886251
SURF	0.2582736
FAST	0.798126
ORB Technique	0.387121

Table 1 and Table 2 show that feature-based methods are much faster than the direct methods. Among the feature-based image stitching algorithms, SURF has better running time performance.

7. Summary of Registration and Blending Methods

The summary of different registration algorithms as image blending used for image stitching is given in Table 3 and Table 4, respectively. This table narrates the methods and the advantages and disadvantages of different image registration and blending methods.

Table 3. Summary of some registration methods for image stitching

Method	Advantages	Disadvantages
Correlation-based	Pixel-wise comparison is needed. No high-level structural analysis is required.	Suitable for stitching images that are related by 2D translation only. Not Scale and rotation invariant
Fourier based method	Registration speed is high	Not scale, rotation and affine invariant
Mutual Information based	It is good for multimodal examination, and it is less vulnerable to changes in illumination and occlusion.	When the overlapping area is limited, the process becomes slow, and there may be a chance of registration errors.
Harris Corner detector	Detects corner features, Rotation invariant, High repeatability rate, location accuracy, robustness and efficiency, Precise computation	Only works for small changes in Scale and rotation and needs advanced knowledge of window size. Not scale and affine invariant.
Smallest Univalued Segment Assimilating Nucleus (SUSAN)	Resistant to noise, high detection rate and speed	Invariance is not considered.
Maximally Stable Extremal Region (MSER)	Region detector, scale, rotation, and affine transformation invariant	can't detect corner features.
Scale Invariant Feature Transform (SIFT) descriptor and its variants	Detects corner and blob features. It's good for high-resolution images and has translation, size, and rotation invariance.	Computational cost is high because of the high dimension of the feature vector. Not Affine invariant.
Feature from Accelerated Segment Test (FAST)	Calculations that are both precise and very fast	The performance will reduce if high noise levels are present, and prior threshold awareness is mandatory.
Speeded Up Robust Features (SURF)	Detects corners and blob features, Fast computing is beneficial for real-time applications. Scale and rotation invariant.	Poor performance under colour and illumination changes. Not affine invariant
Oriented FAST and Rotated BRIEF (ORB Technique)	good performance, low cost, noise-tolerant and rotation invariant	Scale change is not considered in the original work.

Table 4. Summary of some image blending techniques

Blending technique	Advantages	Disadvantages
Feathering blending	Under different exposures, quick and good performance is possible.	Blur and ghosting effects are common in the final image
Pyramid blending	Effective for avoiding blur and edge duplication.	When there is a severe registration problem, it suffers from double contouring and ghosting.
Gradient blending[21]	The visually more appealing output than previous approaches. When there are variations in exposure, the transition is clear.	Good performance requires high computation, and if registration errors are large, the performance will reduce.
Optimal seam blending	It's good at handling moving objects and parallax errors.	In the case of exposure variation, the transition is clear.

8. Discussion and Conclusion

The major steps of image stitching are calibration, registration and blending. The image stitching algorithms can be classified based on the registration methods used. The main two categories are a direct method and a feature-based method. A comparison between different types of direct methods and feature-based methods is done in this paper. A comparison of different blending algorithms is also performed. Direct methods use pixel intensity values to measure the similarity, so these methods cannot handle scaling and rotation in source images. The feature-based methods use features of images for image matching. The performance of the feature-based methods decreases when the illumination changes. The computation cost is also high for all the image stitching methods discussed here. Therefore, this review of literature reflects the wide scope of image stitching.

9. Challenges, Open Issues and Future Directions

Image stitching has a wide variety of uses, making it a hot subject in computer vision and image understanding science. Several fundamental methods of image stitching are discussed in this article. Using the combination of best feature extraction methods and blending algorithms makes it possible to create a robust and efficient image stitching method. The literature review reveals that some limitations are present in the existing methods. Even commercial tools are available for stitching images to form a panorama. Still, there are many obstacles and unexplored possibilities.

One of the challenges in image stitching is to make fully automated stitching algorithms to create a reliable panorama. It is tough to eliminate matching false feature points while creating the panorama. Moving object identification and proper alignment are also very challenging tasks. The stitching method must be robust to outliers like moving objects. This issue can be solved by applying good machine learning algorithms to identify the matching features and testing them to improve scene interpretation. De-ghosting techniques can frequently be effectively masking modest quantities of parallax by warping algorithms and seam selection. The stitched images may sometimes distort or misaligned. It is impossible to predict when the alignment error will occur. Many input images may lead to a high processing time for stitching. The main challenges of image stitching are listed below:

9.1 Wide Baseline and Large Parallax

In contrast to the professional image capturing technologies, the image captured by handheld cameras is acquired more flexibly and casually. Due to the free movement of cameras, while capturing images, there is a chance for noise and blur effects in the input images. Many complications arise due to the angle and exposure differences between cameras, such as a broad baseline, high parallax, and brightness differences. This will result in large parallax errors in the input images. The accuracy of the stitching algorithm will decrease with an increase in the parallax errors in the input images[57].

9.2 Low-texture Overlapping Regions

In some images, some patches have low-texture information. It's tough to stitch well in images with huge background areas, such as images of floors with the same pattern or a single landscape in a natural scene like the image of sky, flower, sea, lake, and forest [58]. Stitching images with the low-texture overlapping region is a challenging task.

9.3 Very Wide Baseline and Very Large Parallax

Modern surveillance systems commonly use image stitching algorithms for combining multiple images. The irregular positions of surveillance cameras result in a very wide baseline. The distance between the cameras maybe a few meters or more than ten meters. This will result in a wide baseline. For example, in the case where cameras are arranged in a square, resulting in the minimal overlap between images. The distance between the cameras and the target source is usually quite short, resulting from many parallaxes in the input images. So, it's challenging to stitch images from a wide baseline and images with large parallax. This will result in inaccurate transformations between images and registration errors. So, we intend to solve the existing limitation of image stitching methods by developing a novel method for stitching overlapping images and the method that is invariant to translation, scaling, rotation, illumination changes and viewpoint changes.

References

[1] Y. Yuan, F. Fang, and G. Zhang, Superpixel-Based Seamless Image Stitching for UAV Images, IEEE Trans. Geosci. Remote Sensing. 59(2) (2021) 1565–1576. doi: 10.1109/TGRS.2020.2999404.

[2] T. Zhang, R. Zhao, and Z. Chen, Application of Migration Image Registration Algorithm Based on Improved SURF in Remote Sensing Image Mosaic, IEEE Access. 8 (2020) 163637–163645. doi: 10.1109/ACCESS.2020.3020808.

[3] Y. Zhang, Z. Wan, X. Jiang, and X. Mei, Automatic Stitching for Hyperspectral Images Using Robust Feature Matching and Elastic Warp, IEEE J. Sel. Top. Appl. Earth Observations Remote Sensing. 13 (2020) 3145–3154. doi: 10.1109/JSTARS.2020.3001022.

[4] V. Megha and K. K. Rajkumar, Automatic Satellite Image Stitching Based on Speeded Up Robust Feature, in 2021 International Conference on Artificial Intelligence and Machine Vision (AIMV). (2021) 1–6. doi: 10.1109/AIMV53313.2021.9670954.

[5] B. Ma et al., A Fast Algorithm for Material Image Sequential Stitching, Computational Materials Science. 158 (2019) 1–13. doi: 10.1016/j.commatsci.2018.10.044.

[6] S. Mistry and A. Patel, Image Stitching using Harris Feature Detection. 3(4) 7.

[7] F. Yang, Z.-S. Deng, and Q.-H. Fan, A Method for Fast Automated Microscope Image Stitching, Micron. 48 (2013) 17–25. doi: 10.1016/J.Micron.2013.01.006.

[8] A. Pandey and U. C. Pati, A Novel Technique for Non-Overlapping Image Mosaicing Based on Pyramid Method, in 2013 Annual IEEE India Conference (INDICON), Mumbai, India. (2013) 1–6. doi: 10.1109/INDCON.2013.6726136.

[9] D. Ghosh, N. Kaabouch, and R. A. Fevig, Robust Spatial-Domain Based Super-Resolution Mosaicing of Cubesat Video Frames: Algorithm and Evaluation, CIS. 7(2) (2014) 68. doi: 10.5539/Cis.V7n2p68.

[10] R. Szeliski, Image Alignment and Stitching: A Tutorial, FNT in Computer Graphics and Vision. 2(1) (2007) 1–104. doi: 10.1561/0600000009.

[11] P. Baudisch et al., Panoramic Viewfinder: Providing a Real-Time Preview to Help Users Avoid Flaws in Panoramic Pictures. 10.

[12] M. D. Kokate, Survey: Image Mosaicing Based on Feature Extraction, International Journal of Computer Applications. 165(1) 5.

[13] B. A and D. T. KK, Analytical Study on Digital Image Processing Applications, SSRG-IJCSE. 7(6) (2020) 4–7. doi: 10.14445/23488387/IJCSE-V7I6P102.

[14] J. Mallon and P. F. Whelan, Calibration and Removal of Lateral Chromatic Aberration in Images, Pattern Recognition Letters. 28(1) (2007) 125–135. doi: 10.1016/j.patrec.2006.06.013.

[15] Z. Zhang, A Flexible New Technique for Camera Calibration, IEEE Trans. Pattern Anal. Machine Intell. 22(11) (2000) 1330–1334. doi: 10.1109/34.888718.

[16] J. Zhu, Y. Li, C. Liu, Z. Ma, and B. Zhang, Research on Calibration Method of the Panoramic Stereo Sphere Vision System, in 2015 IEEE International Conference on Mechatronics and Automation (ICMA), Beijing, China. (2015) 2346–2351. doi: 10.1109/ICMA.2015.7237853.

[17] M. H. M. Patel and A. P. J. Patel, Comprehensive Study and Review of Image Mosaicing Methods, International Journal of Engineering Research. 1(9) (2012) 7.

[18] L. Juan and O. Gwun, A Comparison of SIFT, PCA-SIFT and SURF. 10.

[19] L. G. Brown, A Survey of Image Registration Techniques, ACM Comput. Surv. 24(4) (1992) 1325–376. doi: 10.1145/146370.146374.

[20] J. Salvi, C. Matabosch, D. Fofi, and J. Forest, A Review of Recent Range Image Registration Methods with Accuracy Evaluation, Image and Vision Computing. 25(5) (2007) 578–596. doi: 10.1016/J.Imavis.2006.05.012.

[21] Y. Deng and T. Zhang, Generating Panorama Photos, Orlando, FL. (2003) 270–279. doi: 10.1117/12.513119.

[22] Y. Xiong and K. Pulli, Gradient Domain Image Blending and Implementation on Mobile Devices, in Mobile Computing, Applications, and Services, T. Phan, R. Montanari, and P. Zerfos, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg. 35 (2010) 293–306. doi: 10.1007/978-3-642-12607-9_19.

[23] Y. Xiong and K. Pulli, Mask-Based Image Blending and its Applications on Mobile Devices, Yichang, China. (2009) 749841. doi: 10.1117/12.832379.

[24] D. Ghosh and N. Kaabouch, A Survey on Image Mosaicing Techniques, Journal of Visual Communication and Image Representation. 34 (2016) 1–1. doi: 10.1016/j.jvcir.2015.10.014.

[25] J. P. W. Pluim, J. B. A. Maintz, and M. A. Viergever, Mutual-Information-Based Registration of Medical Images: A Survey, IEEE Trans. Med. Imaging. 22(8) (2003) 986–1004. doi: 10.1109/TMI.2003.815867.

[26] S.-D. Wei and S.-H. Lai, Fast Template Matching Based on Normalized Cross Correlation with Adaptive Multilevel Winner Update, IEEE Trans. on Image Process. 17(11) (2008) 2227–2235. doi: 10.1109/TIP.2008.2004615.

[27] Y. Douini, J. Riffi, M. A. Mahraz, and H. Tairi, Solving Sub-Pixel Image Registration Problems Using Phase Correlation and Lucas-Kanade Optical Flow Method. 5.

[28] M. V and R. KK, Panoramic Image Stitching Using Cross Correlation and Phase Correlation Methods, IJCS. 8(2) (2020) 2500–2516.

[29] D. Baran, N. Fung, S. Ho, and J. Sherman, Detecting and Tracking Humans Using a Man-Portable Robot, Orlando, Florida, USA. (2009) 733215. doi: 10.1117/12.818813.
[30] J. Chen, Q. Wan, L. Luo, Y. Wang, and D. Luo, Drone Image Stitching Based on Compactly Supported Radial Basis Function, IEEE J. Sel. Top. Appl. Earth Observations Remote Sensing. 12(11) (2019) 4634–4643. doi: 10.1109/JSTARS.2019.2947162.
[31] C. Harris and M. Stephens, A Combined Corner and Edge Detector, in Proceedings of the Alvey Vision Conference 1988, Manchester. (1988) 23.1-23.6. doi: 10.5244/C.2.23.
[32] S. M. Smith and J. M. Brady, SUSAN—A New Approach to Low Level Image Processing. (1997) 34.
[33] K. Sharma and A. Goyal, Classification Based Survey of Image Registration Methods, In 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), Tiruchengode. (2013) 1–7. doi: 10.1109/ICCCNT.2013.6726741.
[34] D. G. Lowe, Distinctive Image Features from Scale-Invariant Keypoints, International Journal of Computer Vision. 60(2) (2004) 91–110. doi: 10.1023/B: VISI.0000029664.99615.94.
[35] E. Adel, M. Elmogy, and H. Elbakry, Image Stitching Based on Feature Extraction Techniques: A Survey, IJCA. 99(6) (2014) 1–8. doi: 10.5120/17374-7818.
[36] H. Bay, T. Tuytelaars, and L. Van Gool, SURF: Speeded Up Robust Features, in Computer Vision – ECCV 2006, A. Leonardis, H. Bischof, and A. Pinz, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg. (3951) (2006) 404–417. doi: 10.1007/11744023_32.
[37] A. V. Kulkarni, J. S. Jagtap, and V. K. Harpale, Object Recognition with ORB and its Implementation on FPGA, International Journal of Advanced Computer Research.3(3) 6.
[38] E. Rosten and T. Drummond, Machine Learning for High-Speed Corner Detection, in Computer Vision – ECCV 2006, A. Leonardis, H. Bischof, and A. Pinz, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg. (3951) (2006) 430–443. doi: 10.1007/11744023_34.
[39] M. A. Fischler and R. C. Bolles, Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography, in Readings in Computer Vision, Elsevier. (1987) 726–740. doi: 10.1016/B978-0-08-051581-6.50070-2.
[40] N. Arad and D. Reisfeld, Image Warping Ra Udsiianlg Ffuenwct Aionncshor Points and. (1994) 12.
[41] Yalin Xiong and K. Turkowski, Registration, Calibration and Blending in Creating High Quality Panoramas, In Proceedings Fourth IEEE Workshop on Applications of Computer Vision. WACV'98 (Cat. No.98EX201), Princeton, NJ, USA. (1998) 69–74. doi: 10.1109/ACV.1998.732860.
[42] Yanfang Li, Yaming Wang, Wenqing Huang, and Zuoli Zhang, Automatic image stitching using SIFT, in 2008 International Conference on Audio, Language and Image Processing, Shanghai, China. (2008) 568–571. doi: 10.1109/ICALIP.2008.4589984.
[43] W. Rong, H. Chen, J. Liu, Y. Xu, and R. Haeusler, Mosaicing of Microscope Images Based on SURF, in 2009 24th International Conference Image and Vision Computing New Zealand, Wellington, New Zealand. (2009) 271–275. doi: 10.1109/IVCNZ.2009.5378399.
[44] D. K. Jain, G. Saxena, and V. K. Singh, Image Mosaicing Using Corner Techniques, in 2012 International Conference on Communication Systems and Network Technologies, Rajkot, Gujarat, India. (2012) 79–84. doi: 10.1109/CSNT.2012.27.
[45] M. Vivet, S. Peleg, and X. Binefa, Real-Time Stereo Mosaicing Using Feature Tracking, in 2011 IEEE International Symposium on Multimedia, Dana Point, CA, USA. (2011) 577–582. doi: 10.1109/ISM.2011.102.
[46] B. Baheti, U. Baid, and S. N. Talbar, A Novel Approach for Automatic Image Stitching of Spinal Cord MRI Images Using SIFT, in 2015 International Conference on Pervasive Computing (ICPC), Pune, India. (2015) 1–5. doi: 10.1109/PERVASIVE.2015.7087071.
[47] S. Keerativittayanun, T. Kondo, K. Kotani, T. Phatrapornnant, and J. Karnjana, Two-Layer Pyramid-Based Blending Method for Exposure Fusion, Machine Vision and Applications. 32(2) (2021) 48. doi: 10.1007/S00138-021-01175-9.
[48] Y. Xiong, Eliminating Ghosting Artifacts for Panoramic Images, in 2009 11th IEEE International Symposium on Multimedia, San Diego, California, USA. (2009) 432–437. doi: 10.1109/ISM.2009.92.
[49] A. Levin, A. Zomet, S. Peleg, and Y. Weiss, Seamless Image Stitching in the Gradient Domain. 13.
[50] C. Zhu, W. Ding, H. Zhou, and F. Yu, Real-Time Image Mosaic based on Optimal Seam and Multiband Blend, in 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), Chongqing, China. (2019) 722–725. doi: 10.1109/ITAIC.2019.8785712.
[51] M. El-Saban, M. Izz, A. Kaheel, and M. Refaat, Improved Optimal Seam Selection Blending for Fast Video Stitching of Videos Captured from Freely Moving Devices, in 2011 18th IEEE International Conference on Image Processing, Brussels, Belgium. (2011) 1481–1484. doi: 10.1109/ICIP.2011.6115723.
[52] N. Gracias, M. Mahoor, S. Negahdaripour, and A. Gleason, Fast Image Blending Using Watersheds and Graph Cuts, Image and Vision Computing. 27(5) (2009) 597–607. doi: 10.1016/j.imavis.2008.04.014.
[53] Hongyan Wen and Jianzhong Zhou, An Improved Algorithm for Image Mosaic, in 2008 International Symposium on Information Science and Engineering, Shanghai. (2008) 497–500. doi: 10.1109/ISISE.2008.293.
[54] F. Gu and Y. Rzhanov, Optical Image Blending for Underwater Mosaics. 6.
[55] V. S. Bind, P. R. Muduli, and U. C. Pati, A Robust Technique for Feature-Based Image Mosaicing using Image Fusion. 6.

[56] T. S. and A. B., Multiple Feature Extraction Techniques in Image Stitching, IJCA. 123(15) (2015) 29–33. doi: 10.5120/ijca2015905747.
[57] C. Liu, H. Liu, Y. Liu, T. Li, and T. Wang, Normalized Cross Correlation Image Stitching Algorithm Based on Minimum Spanning Tree, Optik. 179 (2019) 610–616. doi: 10.1016/j.ijleo.2018.10.166.
[58] Y. Li, H.-Y. Shum, and R. Szeliski, Stereo Reconstruction from Multiperspective Panoramas, IEEE Transactions on Pattern Analysis and Machine Intelligence. 26(1) (2004) 18.
[59] J. Zheng, Z. Zhang, Q. Tao, K. Shen, and Y. Wang, An Accurate Multi-Row Panorama Generation Using Multi-Point Joint Stitching, IEEE Access. 6 (2018) 27827–27839. doi:10.1109/ACCESS.2018.2829082.