A Review of Image Stitching Methods: From the Original Manual to the Modern Automatic Algorithms.

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Abstract. Image stitching is a fundamental image processing technique that combines multiple overlapping images into panoramic images while minimizing transitions and distortions. This paper explores the evolution of image stitching from its manual beginnings to contemporary automated systems driven by advances in AI. Traditional methods, including direct and feature-based approaches, are discussed, highlighting their strengths and limitations. Recent advancements in AI, particularly in deep learning techniques, have significantly improved the accuracy and robustness of image stitching in complex scenarios. The AutoStitch algorithm is also examined for its comprehensive approach to feature detection, homography estimation, and blending. Despite these advancements, challenges in handling large datasets and poor capture conditions remain. This paper concludes by discussing the potential of emerging techniques to further transform applications in photography, mapping, augmented reality, and beyond.

Keywords: Image Stitching, Panoramic Image Processing, Feature-based methods, Deep learning algorithms, AutoStitch, Computer vision, Image alignment, Optimization Techniques

1 Introduction

Image stitching is a fundamental technique in image processing that combines multiple overlapping images to create wide panoramic or higher-resolution images while minimizing transitions and distortions. This technique has transformed remarkably from its manual beginnings in the 19th century to contemporary automated systems, driven by advances in computer vision and artificial intelligence [1]. In its early days, this process was carried out manually by joining daguerreotypes, which, despite being innovative at the time, had significant limitations [2]: dependence on the operator's skill, lack of geometric precision,

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and the inability to correct perspective differences. However, these rudimentary methods laid the groundwork for developing more sophisticated approaches, which we will explore in this article.

Image stitching methods are usually classified into two groups: *direct methods* and *feature-based methods*. While direct methods use pixel intensity-based alignment techniques to find correspondences between images, feature-based methods detect and match key points (features) between images, such as corners or edges, using algorithms like SIFT (Scale-Invariant Feature Transform) [3] and SURF (Speeded-Up Robust Features) [4]. Both approaches to image stitching have found their way to several applications, including panoramic photography, aerial mapping, virtual reality, specialized medical imaging, and remote sensing.

In recent years, advances in feature detection algorithms, geometric optimization, and artificial intelligence (AI) have expanded the scope of image stitching and improved its accuracy, especially in complex scenarios.

The remaining sections of this paper are organized as follows. Section II presents traditional techniques and their general methodology. New approaches to image stitching, which use AI techniques, are covered in Section III. The AutoStitch algorithm, a fully automated approach to image stitching proposed by Matthew Brown and David G. Lowe, is covered in section IV. Finally, Section V discusses the limitations and possibilities of the image stitching methodologies.

2 Image Stitching methods

Image stitching refers to merging multiple overlapping images into a unified panoramic image. Its main stages could be enumerated as follows: Feature Detection (identifying distinctive points in the images), Feature Matching (locating corresponding points across images), Alignment (applying transformations to align the images), and Blending (seamlessly combining the images).

Methods for image stitching are generally divided into two categories, depending on where the similarities between images are searched: direct methods and feature-based methods. Below, we outline a general algorithm that incorporates both methodologies.

1. **Image Acquisition:**
   - 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[5].
2. **Image Registration:**
   - **Direct Methods:**
     - Direct search for similarities between image regions using methods like cross-correlation or intensity difference minimization[6].
     - Optimization of pixel-based alignment to improve registration accuracy[6].
   - **Feature-Based Methods:**
     - Detection of key features using algorithms like SIFT (Scale-Invariant Feature Transform)[7] or SURF (Speeded-Up Robust Features)[4].

- Matching features between images using techniques like k-nearest neighbors (k-NN)[8].
- Estimation of the homography or geometric transformation to align the images[8].

3. **Image composition (Warping):**
   - Application of the estimated geometric transformation to align the images.
   - Use of interpolation techniques, such as bilinear or bicubic, to smooth the transition between images[7].
4. **Blending:**
   - Combination of the aligned images to create a seamless panoramic image.
   - Common techniques include simple averaging, multi-band blending, or the use of transition masks[6].
5. **Postprocessing:**
   - Removal of artifacts, such as ghosting edges, using smoothing techniques.
   - Adjustment of color and brightness to ensure uniformity in the final image.

Direct methods, also called *pixel-based methods*, directly compare pixel intensity values, allowing for highly precise alignment in controlled conditions. However, they have a high computational cost and are highly sensitive to illumination variations and geometric transformations such as scale, rotation, and perspective changes. On the other hand, feature-based methods extract key points from images and use them for alignment, making them more robust and computationally efficient. These methods are instrumental in real-time applications. However, their performance depends on the quality of the detected key points and their descriptors. The table 1 offers a comparative of both approaches.

Table 1. General Differences Between Direct Methods and Feature-Based Methods

Aspect	**Direct Methods**	**Feature-Based Methods**
Working Principle	Compare pixel intensity values directly between images.	Detect and extract key features (points, edges, corners) for image alignment.
Robustness to Geometric Transformations	Sensitive to scale, rotation, and perspective changes.	Invariant to rotation, scale, and perspective changes.
Tolerance to Illumination and Occlusions	Highly sensitive to illumination variations and occlusions.	More robust to lighting variations and partial occlusions.
Computational Efficiency	Computationally expensive due to pixel-wise operations.	More efficient by reducing dimensionality using descriptors.
Precision	Can achieve highly accurate alignment for images with small variations.	Accuracy depends on the quality of feature detection and matching.
Real-Time Applicability	Less suitable for real-time applications due to high computational cost.	Optimized algorithms like ORB can run in real-time.
Example Algorithms	SAD, SSD, NCC, MI.	SIFT, SURF, ORB, BRISK, FREAK, KAZE, AKAZE.

2.1 Direct Methods

Direct methods include a variety of techniques designed to compare image regions directly. The most commonly used approaches are Sum of Squared Differences (SSD) and Sum of Absolute Differences (SAD), which measure similarity by computing pixel intensity differences. Additionally, correlation-based methods assess the degree of similarity between image patches, while Mutual Information is frequently employed in multimodal image registration to maximize shared information between images. These methods evaluate similarity measures between pixel values, making them particularly effective for processing well-aligned images with minimal distortions [5]. Further details about prominent direct methods are provided in the following paragraphs; their advantages and disadvantages are summarized in Table 2.

Sum of Absolute Difference (SAD). The SAD is a simple and effective method for image stitching, especially when motion estimation is required [9]. It calculates the absolute difference between pixel intensities of two images I_0 and I_1 at different displacements u:

$$\mathrm{SAD}(I_1, I_2) = \sum_{x,y} |I_1(x,y) - I_2(x,y)| \tag{1}$$

A low SAD value indicates good alignment between the two images, helping determine the optimal transformation for stitching.

Sum of Squared Difference (SSD). The SSD is an alternative similarity metric used for alignment. By squaring the pixel intensity differences, SSD emphasizes larger discrepancies more than SAD:

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

Minimizing SSD allows for locating overlapping regions between images, ensuring an accurate alignment[10].

Cross-correlation measures the intensity similarity between two images by computing their dot product:

$$C(I_1, I_2) = \sum_{x,y} I_1(x,y) \cdot I_2(x,y) \tag{3}$$

where $C(m,n)$ represents the correlation value for a displacement (m,n). This method is particularly useful for detecting patterns and aligning images with repetitive textures [10].

Normalized Cross-Correlation (NCC). When brightness variations exist between images, Normalized Cross-Correlation (NCC) provides a more robust solution:

$$\mathrm{NCC}(I_1, I_2) = \frac{\sum_{x,y}(I_1(x,y)-\mu_1)(I_2(x,y)-\mu_2)}{\sqrt{\sum_{x,y}(I_1(x,y)-\mu_1)^2 \sum_{x,y}(I_2(x,y)-\mu_2)^2}} \quad (4)$$

where μ_1 and μ_2 are the mean intensities of I_1 and I_2, respectively. NCC is more robust to illumination changes and noise compared to SAD, SSD, and standard cross-correlation, making it a popular choice for image alignment tasks [10].

Mutual Information (MI). This method evaluates the statistical dependence between image intensities[11]. The MI between two images I_1 and I_2 is given by:

$$\mathrm{MI}(I_1, I_2) = \sum_{i,j} p(i,j) \log \frac{p(i,j)}{p_1(i) \cdot p_2(j)} \quad (5)$$

where $p(i,j)$ is the joint probability distribution of the intensities in I_1 and I_2, and $p_1(i)$ and $p_2(j)$ are the marginal distributions. MI is highly effective for aligning images with different modalities or significant intensity variations, such as in medical imaging.

Table 2. Advantages and Disadvantages of Direct Methods

	Advantages(+) / Disadvantages(−)
Simplicity	(+) Easy to implement.
Computational Cost	(−) High computational cost for high-resolution images.
Noise Robustness	(−) Highly sensitive to noise.
Illumination Invariance	(−) Sensitive to changes in lighting and contrast.
Geometric robustness	(+) Effective for translations and simple affine transformations. (−) Poor performance with rotations, scaling, or complex deformations.
Efficiency in Complex Textures	(+) Ideal for images with uniform textures or few distinctive features. (−) Less effective in images with complex features.
Multimodal Image Alignment	(+) Methods such as Mutual Information (MI) are effective for images from different modalities. (−) Requires precise estimation of probability distributions.
Accuracy in Similar Images	(+) High accuracy in images with strong similarity in intensity and structure. (−) Struggles with images containing occlusions or significant perspective changes.

2.2 Feature-Based Methods

With the advent of computer vision in the 1980s, algorithms emerged that could identify and match key features in images, such as corners, edges, and other key points that are invariant to changes in scale, rotation, and lighting conditions [3]. Some of the most notable examples are briefly described in the following paragraphs.

Scale-Invariant Feature Transform (SIFT). Introduced by Lowe [3], this algorithm identifies robust key points that are invariant to geometric transformations and illumination changes. It uses intensity gradients to create unique descriptors that enable precise matching between images.

Speed-Up Robust Features (SURF). Proposed as an improvement over SIFT by Herbert Bay [4], SURF employs Haar wavelet responses to accelerate the detection and description process. It is particularly effective in applications requiring real-time processing due to its lower computational complexity.

Oriented FAST and Rotated BRIEF (ORB). An efficient alternative to SIFT and SURF, ORB combines the FAST detector and the BRIEF descriptor, optimizing them for speed and robustness while also being invariant to rotation and scale [12].

KAZE and AKAZE. KAZE detects keypoints in nonlinear scale spaces using diffusion equations, which allows for better edge preservation compared to linear methods. AKAZE, on the other hand, is a faster version of KAZE, designed for real-time applications. Both algorithms are particularly useful in scenarios requiring high-precision feature detection [13].

BRISK (Binary Robust Invariant Scalable Keypoints) BRISK identifies keypoints using a circular sampling pattern and determines their orientation based on local gradients. It generates a binary descriptor by comparing intensity pairs within the sampling pattern [14]. This algorithm is well-suited for real-time applications and resource-constrained systems.

FREAK (Fast Retina Keypoint) FREAK employs a retina-inspired sampling pattern to detect keypoints and creates a binary descriptor by comparing pixel pairs within the pattern. This approach mimics the human visual system to enhance efficiency [15]. FREAK is highly efficient and is commonly used in mobile and low-power applications.

Once the features are detected, the next step is to find correspondences between the images. This is achieved by comparing the feature descriptors using distance metrics, such as the Euclidean distance. To improve accuracy, techniques like the following are applied:

1. **Lowe's ratio test:** Filters ambiguous matches by comparing the distance of the nearest neighbor with that of the second nearest neighbor [3].
2. **K-NN (k-Nearest Neighbors):** Finds the k closest matches for each feature [16].
3. **FLANN (Fast Library for Approximate Nearest Neighbors):** Designed to efficiently match large sets of descriptors, FLANN is particularly useful in projects involving high-resolution images.

With the correspondences between images having been found, it is time to estimate the homography, a projective transformation that maps points from one image to another. To estimate it, methods such as the following are used:

1. **RANSAC (Random Sample Consensus):** Fischler and Bolles [17] proposed RANSAC to eliminate outliers and robustly compute the homography. This method filters incorrect matches and randomly selects a subset of points, evaluating their consistency with the model.

The final step is image blending, where the images are projected onto a common plane and combined. The most common techniques include:

1. **Linear averaging:** Combines images by averaging pixel values in overlapping regions [9].
2. **Multi-band blending:** Szeliski [9] proposed this technique, which blends images at multiple frequency bands to avoid discontinuities.
3. **Poisson blending:** Uses differential equations to smooth transitions between images [18].

In addition to feature detection and matching, these techniques include optimization steps such as lens distortion correction and alignment based on homographies. This ensures that the images are assembled with minimal visual inconsistencies. The table 3 summarizes this approach's advantages and disadvantages.

Table 3. Advantages and Disadvantages of Feature-Based Methods

	Advantages(+) / Disadvantages(−)
Computational Cost	(+) Reduces dimensionality by working with descriptors. (−) High computational cost for large images.
Real-Time Applicability	(+) Algorithms like ORB are optimized for real-time processing. (−) Higher implementation complexity.
Illumination Invariance	(+) Robust to changes in lighting conditions. (+)Sensitive to extreme illumination variations.
Geometric Robustness	(+) Invariant to rotations, scaling, and perspective changes. (−) Challenging under extreme scale variations.
Efficiency in Complex Textures	(+) Ideal for images with rich textures and distinctive features. (−) Less effective in images with uniform textures.
Handling of Occlusions	(+) Can manage partial occlusions. (−) Struggles with significant occlusions.

3 Emerging Techniques

Image stitching has significantly advanced through artificial intelligence (AI) techniques, mainly thanks to deep learning models that learn patterns directly from data, reducing reliance on manually crafted descriptors [19]. Beyond convolutional neural networks (CNNs), other AI approaches have been explored to enhance image stitching. For instance, Generative Adversarial Networks (GANs) have been employed to improve blending and artifact reduction, ensuring seamless transitions in stitched images [20]. Additionally, transformer-based models have been investigated for their ability to capture long-range dependencies, aiding in more accurate image alignment [21]. These advancements demonstrate how AI, beyond traditional CNNs, is revolutionizing image stitching by making it more robust, adaptive, and efficient across various applications, including medical imaging, satellite image mosaicking, and real-time panoramic video generation [19].

Among the different ways in which AI has enhanced the different stages of image stitching, we can highlight the following:

- **Feature Detection with CNNs:** They replace traditional methods like SIFT, generating more accurate keypoints. For example:
  - **SuperPoint:** It is a neural network that detects and describes keypoints in images. SuperPoint is trained in a self-supervised manner and outperforms traditional methods like SIFT in terms of accuracy and robustness. It was proposed by Detone in 2018 [22].
  - **LF-Net:** It is a neural network that jointly detects and describes features using a deep learning-based approach. Proposed by Ono et al. in 2018 [23].
- **Homography Estimation with Neural Networks:** Homography estimation has also benefited from deep learning. Some methods include:
  - **Unsupervised Homography Estimation:** Nguyen et al. (2018) [24], proposed an unsupervised method that trains a CNN using photometric consistency as the loss function. This eliminates the need for labeled homography data.
  - **DSAC (Differentiable Sample Consensus):** Proposed by Brachmann et al. (2017) [25], DSAC integrates RANSAC into a neural network, making the entire pipeline differentiable. This allows end-to-end training while maintaining the robustness of RANSAC.
- **Image Fusion with Deep Learning:**
  - **Deep Blending:** Uses a neural network to seamlessly blend images, minimizing discontinuities in overlapping regions [26].
  - **GAN-based Image Stitching:** Generative adversarial networks (GANs) have been used to generate realistic transitions between images. For example, Ma et al. [27] proposed a GAN-based method for medical image fusion, where the generator learns to produce fused images and the discriminator ensures their quality.

These modern techniques have significantly advanced the field of image fusion, offering improved quality, robustness, and adaptability compared to traditional methods. Techniques like CNN-based fusion and GANs have enabled new applications in medical imaging, remote sensing, and multi-modal fusion. However, challenges remain, particularly in terms of data requirements, generalization, and computational cost.

4 Automatic Panoramic Image Stitching

The AutoStitch algorithm [7], introduced by Matthew Brown and David G. Lowe in 2007, is one of the most influential methods in the field of panorama creation from multiple images. This algorithm relies on local feature detection using the SIFT (Scale-Invariant Feature Transform) descriptor and robust homography estimation through the RANSAC (Random Sample Consensus) algorithm. The overall operation of the algorithm could be summarized in the following steps:

1. **Feature Detection:** The algorithm employs the SIFT feature detector [3] to identify keypoints in each image. These keypoints are invariant to changes in scale and rotation, enabling the handling of images with varying orientations and zoom levels. Feature matching between image pairs is then performed using Lowe's ratio test, which eliminates false matches by comparing the distance between the two nearest neighbors in the feature space.
2. **Image Alignment and Homography Estimation:** A probabilistic model is used to estimate the geometric transformation (homography) between image pairs. RANSAC (Random Sample Consensus) is employed to robustly fit the homography and reject outliers.
3. **Bundle Adjustment:** Global alignment is achieved using bundle adjustment, which optimizes the camera parameters and image positions to minimize reprojection errors across all images.
4. **Blending and Compositing:** Multi-band blending is used to seamlessly merge images while minimizing ghosting and exposure differences. This technique blends images at multiple frequency bands, ensuring smooth transitions in both high-frequency details and low-frequency color gradients.

The AutoStitch approach combines robustness and efficiency, establishing itself as a comprehensive solution for image stitching. Its ability to handle complex transformations and produce seamless panoramas has made it a benchmark in the field.

5 Conclusion

Image stitching has evolved significantly from its manual origins to modern algorithms powered by deep learning. Traditional methods, such as direct and feature-based approaches, have laid the groundwork for more sophisticated techniques, enabling precise alignment and seamless blending of images. The introduction of deep learning, mainly through convolutional neural networks (CNNs) and generative adversarial networks (GANs), has further enhanced the robustness, accuracy, and adaptability of image stitching, making it applicable to a wide range of scenarios, including medical imaging, remote sensing, and real-time panoramic video generation. The AutoStitch algorithm bridges traditional and advanced approaches, integrating feature detection, homography estimation, and blending to produce high-quality panoramas. However, challenges such as handling large datasets, adapting to adverse capture conditions, and reducing computational costs remain. Continued advancements in this field promise to further revolutionize applications in photography, mapping, augmented reality, and beyond, making image stitching an increasingly powerful tool in computer vision and image processing.

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