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A Novel Keypoint-based Image Stitching with Sharpening Technique for High Quality Stitched Image Generation

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***Abstract*—This paper proposes a novel approach to image stitching and sharpening that makes use of powerful keypoint extraction and matching techniques. For precise keypoint detection, the Scale-Invariant Feature Transform (SIFT) technique is used, while the Random Sample Consensus (RANSAC) approach generates homography, which improves alignment across input pictures. Keypoint matching creates correspondences in overlapping regions, allowing for more accurate alignment. To increase image quality, the approach utilises a novel sharpening process that draws on localised information from aligned keypoints. The experimental results show that the approach is effective in producing more precise images and accomplishing accurate image stitching. This method is a major contribution to the area, with applications in various areas such as Mars rover research, computer vision, remote sensing, and general image stitching.**

***Index Terms*—Image stitching, keypoint extraction, SIFT algorithm, Ransac algorithm, homograph, keypoint matching, image sharpening, histogram equalization, computer vision;**

I. INTRODUCTION

Image stitching is a computational process used in computer vision to seamlessly combine multiple images into a single, panoramic or wide-angle image [3]. This technique is widely applied in photography, satellite imaging, and medical imaging. In computer vision and image processing, image alignment and sharpening are basic operations [6]. Our research presents a new keypoint-based strategy as a paradigm shift in response to these issues.

Key Points, being distinctive features within an image, provide a special basis for lining up and refining [4]. Our method makes use of the local information included in key points to provide stronger alignment and sharpening on a variety of image formats.

Our paper explores the limitations of current picture alignment and sharpening approaches, demonstrating a compelling need for a transformative approach. This introduction sets the stage for our revolutionary technique, which is based on the use of keypoints, which are distinct elements within images that give a rich foundation for alignment and refinement.

One unique feature of our approach is the way that keypoint-based alignment and sharpening work together. Our goal is to improve the overall visual acuity of the images while simultaneously addressing alignment flaws through a smooth integration of these two processes. This dual-purpose strategy simplifies the image processing pipeline and creates opportunities for applications in areas including computer-aided design, remote sensing, and medical imaging.

The present study commences with an examination of the current state of image alignment and sharpening, pinpointing the constraints that drive our innovative methodology. After that, we explore the theoretical foundations of our approach, explaining the reasoning behind the use of keypoints as well as the complexities of the suggested alignment and sharpening algorithms and techniques.

II. LITERATURE REVIEW

1) A Brief Overview of Image Stitching: A computer vision technique called image stitching combines several images to create a smooth panorama. Virtual reality, medical imaging, and panoramic photography are just a few of its uses. The difficulties include non-linear distortions, viewpoint shifts, and lighting variations, which call for complex algorithms for reliable and accurate stitching.
2) Traditional Approaches: Feature-based matching, homography estimation, and bundle adjustment were the main emphasis of the early image stitching methods. These methods have shortcomings, such as sensitivity to outliers and lack of robustness when handling a variety of image sets, even though they are effective in some situations.

3) Feature Matching and Extraction: Recent advancements in image stitching have seen improvements in feature extraction and matching algorithms. Key algorithms that efficiently identify distinctive keypoints and match them across images include SIFT (Scale-Invariant Feature Transform), SURF (Speeded Up Robust Features), and ORB (Oriented FAST and Rotated BRIEF). These algorithms have improved the accuracy and robustness of stitching.
4) Optimization Techniques: RANSAC (Random Sample Consensus) is one of the most important optimization techniques that has improved parameter estimation and increased the dependability of image stitching algorithms. These techniques aid in the removal of outliers and improve the accuracy of the stitching output.
5) Advanced Approaches: Convolutional neural networks (CNNs) play a major role in emerging approaches that make use of deep learning. Deep learning techniques facilitate end-to-end stitching, the learning of hierarchical features, and the more efficient handling of complex scenarios.
6) Case Studies and Applications: Applications for image stitching can be found in many domains, including virtual reality, surveillance, and medical imaging. Case studies show how image stitching has been successfully applied in particular fields, highlighting its adaptability and efficacy in a range of real-world situations.
7) Evaluation and Comparative Metrics: It is possible to assess the effectiveness of image stitching techniques by utilizing metrics like robustness, processing speed, and accuracy. Researchers and practitioners are able to select the best algorithms for particular applications with the aid of comparison studies based on these metrics. Standardized benchmarks for evaluating algorithm performance are provided by evaluation datasets that are frequently used.

III. Methodology

The proposed work involves an elaborate image stitching method that makes use of computer vision capabilities. First, two images are loaded and converted to grayscale and RGB formats. The Scale-Invariant Feature Transform (SIFT) technique is then performed on both pictures to detect keypoints and descriptors [8]. The keypoints are visualised on the original RGB photos, and a Brute-Force Matcher is used to locate keypoint matches between the two images, with a ratio test used for quality selection [5]. This BF Matcher involves comparing each feature in one set to every feature in another set and finding the best matches, the ratio test is a refinement step applied to it. Random Sample Consensus (RANSAC) algorithm is used to estimate the homography matrix [7] for image alignment in an accurate way [2]. This includes choosing random sets of keypoints iteratively, computing the homography matrix, and confirming its accuracy [2]. Inlier matches are found using a predefined threshold and displayed on a combined image. Following that, picture stitching occurs, in which the image hues are modified for easier handling and the homography matrix is utilized to transform and overlap the images. A Laplacian sharpening filter with an adjustable blending factor is used to improve the clarity of the stitched image [1]. Then after a histogram equalization is applied to the image to enhance the contrast by redistributing the intensity values [1]. The finished image is a smoothly stitched and sharpened image that combines the input images simply. The proposed method offers a reliable method for image stitching and sharpening, with potential applications in panoramic photography, mars rover images and image synthesis.

IV. Proposed Scheme

In this section, we discuss the proposed algorithm. Here, we tried to give step-wise details of how the images are loaded, how they got matched and the techniques applied to the set of images.

A. Proposed Algorithm

These are the steps involved in the process of Stitching and Sharpening of the given two input images.

1) Read images: Load two RGB images, say R_C and L_C of size $M \times N$ pixels. Further, convert these two images into corresponding grayscale images, say R_G and L_G respectively.
2) SIFT feature extraction: Apply SIFT feature extraction on R_G and L_G to get the keypoints and the feature vectors, F_R and F_L respectively.
3) Feature matching:
   - We use a Brute-Force Matcher to find matching points between two images, F_R and F_L. This method considers all possible matches and ranks them. Then, we apply a simple test: the ratio of the distance of the best match to the distance of the second-best match. If this ratio is below a certain value (threshold), we consider it a good match. This helps us identify reliable correspondences between points in the two images.
   - This threshold is a tuning parameter that determines the sensitivity of the matching algorithm – a lower threshold may result in fewer but more reliable matches, while a higher threshold may allow more matches, but they may be less accurate.

$$\text{GoodMatches} = \left\{ m \in \text{Matches} \mid \frac{\text{distance}_{\text{best}}}{\text{distance}_{\text{second-best}}} < \text{threshold} \right\} \quad (1)$$

   - Equation (1) defines a set of ”GoodMatches” as matches (m) with a ratio of the distance of the best match to the distance of the second-best match below a specified threshold. This ratio test ensures that only reliable keypoint matches are included in the set.
4) Homography Estimation: Homography (say H) is a mathematical transformation capturing the correspondence between keypoints in two images, commonly

applied in computer vision for tasks like image stitching. RANSAC (Random Sample Consensus) is a robust algorithm used to identify the optimal model from a data frame with outliers, achieved through the iterative fitting of models to randomly sampled subsets.

5) RANSAC Iterations: The process involves these iteration (steps)
   - Randomly select a set of four matches.
   - Compute the homography matrix (H) using the selected keypoints.
   - Check if H is valid, by avoiding the division by zero and ensuring the rank is at least 3.
   - Compute the error for all matches using the estimated H.
   - Identify inliers based on a specified threshold.
6) Visualize Inliers: Display the inlier matches on the combined image ($final_{img}$).
7) Stitching Images: The process involves the following steps to achieve $final_{img}$
   - Convert image intensities to double and normalize for better handling.
   - Compute the transformed corners of the left image using the estimated homography.
   - Adjust the homography matrix for translation to handle negative coordinates.
   - Determine the size of the stitched image based on the transformed corners.
   - Warp both images using the adjusted homography matrices.
   - Perform blending/stitching by averaging pixel values where both images contribute.
8) Sharpening Image:
   - Apply the Laplacian Sharpening Filter
     – The Laplacian Sharpening Filter is a mathematical operation that emphasizes rapid changes in intensity, enhancing image features.
   - Define a Laplacian kernel.
     – A Laplacian kernel is a small matrix that specifies the weights for the convolution operation. It is designed to highlight areas of rapid intensity change.
   - Convolve the image with the Laplacian kernel.
     – Convolution involves overlaying the Laplacian kernel on the image and computing the weighted sum of pixel values. This process enhances edges and fine details.
   - Add the result to the original image to get the sharpened image.
     – Combining the result of the convolution with the original image helps accentuate edges while preserving the overall image structure. This additional operation brings out the enhanced features in the sharpened image.
9) Histogram Equalization: The procedure involves converting the sharpened image to grayscale which is essential to ensure a uniform representation of intensity values and simplifying subsequent histogram computations. Then computing the histogram of the image provides a visual summary of pixel intensity distribution, aiding in the analysis of image contrast and potential application of enhancement techniques.

$$H(i) = \sum_{x,y} \delta(I(x,y) - i) \tag{2}$$

   The equation (2) says:
   - $H(i)$ represents the frequency of pixel intensity i in the image.
   - $I(x, y)$ is the pixel intensity at position (x, y) in the image.
   - $\delta(\dots)$ is the Kronecker delta function, which is 1 if the condition inside is true and 0 otherwise.
   - The sum is taken over all pixel positions (x, y) in the image.
10) CDF Calculation: Compute the cumulative distribution function (CDF) of the histogram.The Cumulative Distribution Function (CDF) of a histogram represents the cumulative probability distribution of pixel intensities in an image.
    - Normalization involves scaling the pixel values of an image to a specific range, often [0, 1] or [0, 255], to ensure consistent and standardized intensity representation. This aids in preventing saturation or loss of information due to varying intensity scales.
    - Apply Histogram equalization to the image using the normalized CDF. Equalization, on the other hand, adjusts the distribution of pixel intensities across an image, enhancing overall contrast.
    - Convert the equalized image back to unit8. This conversion is commonly performed in image processing to ensure that pixel values fall within the range, which is the typical representation for images with 8-bit depth.
11) Display Final Image: Visualize the stitching of the image by displaying the final image. Utilize the matplotlib library to showcase the seamlessly stitched and sharpened image, providing a comprehensive view of the enhanced visual outcome. This step serves as the conclusive presentation, allowing for a holistic appreciation of the applied image stitching techniques.

B. Results and Discussion

Fig. 1. Grayscale Image of input images.

The input images undergo a process of combination and subsequent conversion into grayscale to facilitate the application of the SIFT algorithm. This process aims to extract distinctive features from the images, enhancing their compatibility with the SIFT-based analysis.

Fig. 2. Detected the inliers using RANSAC technique

Utilizing the RANSAC technique is pivotal for detecting and emphasizing inliers, a crucial aspect in achieving precise model fitting. By selectively disregarding outliers or points with potential mismatches between the two images, this technique significantly contributes to the accurate computation of the homography matrix.

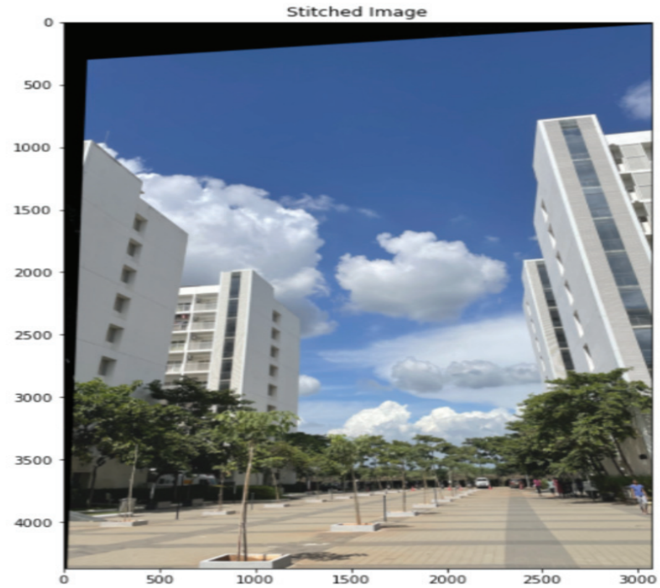

Fig. 3. Stitched Image using Homography matrix

The Stitching of the two input images in the $final_{i}mage$ involves a wrapping and overlapping process facilitated by the homography matrix. This matrix ensures accurate image transformation, aligning the images seamlessly and culminating in a visually cohesive stitched image.

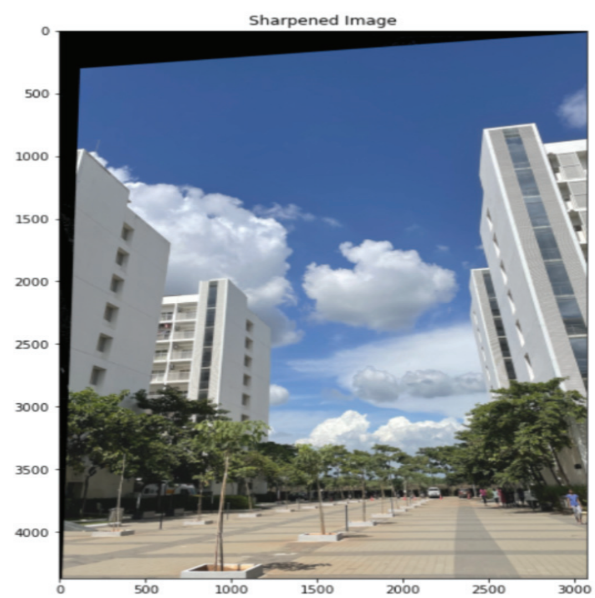

Fig. 4. Sharpened Image

The enhancement of the Stitched Image is achieved through the Sharpened Image, achieved by the application of the Laplacian Sharpening filter. This processing stage aims to accentuate details and elevate the overall image quality, culminating in a visually refined and sharper representation.

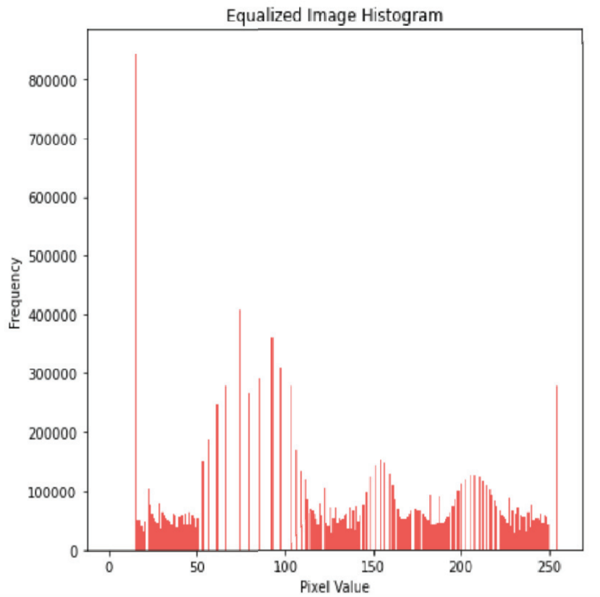

Fig. 5. Applied Histogram Equalization to the Sharpened Image

The symmetry observed in the histogram signifies a balance in pixel values both above and below the median. The unimodal characteristic, marked by a singular peak, hints at a prevailing color or brightness level in the image. Additionally, the extended right tail of the histogram implies the notable presence of pixels with high values, suggesting the existence of bright areas within the image.

V. Conclusion

In conclusion, the proposed image stitching method presents a comprehensive approach using computer vision techniques, specifically utilizing the Scale-Invariant Feature Transform (SIFT) for keypoint detection and matching. The inclusion of a Brute-Force Matcher with a ratio test ensures the selection of high-quality keypoint matches between the two input images. The use of the Random Sample Consensus (RANSAC) algorithm for estimating the homography matrix enhances the accuracy of image alignment. Furthermore, the incorporation of a Laplacian sharpening filter with an adjustable blending factor contributes to improving the clarity of the stitched image. The subsequent application of histogram equalization enhances the contrast by redistributing intensity values, resulting in a smoothly stitched and sharpened final image. The proposed methodology demonstrates its potential reliability in image stitching and sharpening, with practical applications in panoramic photography, Mars rover images, and image synthesis. Overall, the combination of key techniques in this methodology offers a robust solution for creating seamlessly stitched and enhanced images, addressing challenges in alignment, clarity, and contrast. The method holds promise for various applications, making it a valuable contribution to the field of computer vision and image processing.

VI. Future Work

In our current algorithm, we have successfully integrated images, producing aesthetically appealing results. In future, we would like to explore advanced approaches beyond SIFT, like deep learning, for enhanced feature extraction in diverse scenarios. Fine-tune RANSAC parameters to improve homography estimation and keypoint matching accuracy. Investigate advanced preprocessing for smoother and visually pleasing panoramas. Integrate real-time stitching and user-friendly interfaces for broader accessibility. Study advanced enhancement techniques, like tone mapping, to improve visual quality in stitched panoramas.

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