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# ROBUST ALIGNMENT FOR PANORAMIC IMAGE STITCHING VIA AN EXACT RANK CONSTRAINT

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**ABSTRACT**
This project introduces an automated method for stitching panoramic images by leveraging machine learning and computer vision technologies. Traditional methods often require manually sorted images, which can be time-consuming and error-prone. The proposed system eliminates this dependency by automatically identifying and grouping related images based on visual similarity. Feature detection is performed using the Scale- Invariant Feature Transform (SIFT) algorithm, which extracts robust keypoints unaffected by scale, rotation, or lighting variations. These keypoints are matched between image pairs using nearest-neighbor techniques, and the Random Sample Consensus (RANSAC) algorithm is applied to compute accurate homography matrices while filtering out outliers.Once the transformation matrices are obtained, the images are geometrically aligned and warped into a common coordinate space to form a cohesive panorama. Image blending techniques such as multi-band blending or feathering are employed to ensure smooth transitions across image boundaries, minimizing visible seams and exposure differences. The system also integrates quality assessment metrics to evaluate the alignment accuracy and overall visual coherence of the stitched panorama. To enhance scalability, the approach supports batch processing of large image datasets and can adapt to unordered or variably illuminated inputs. Potential applications of this system include automated mapping, virtual tours, surveillance systems, and content generation in augmented reality environments.



## I. INTRODUCTION

Frequent travel for work or leisure often leads to the accumulation of numerous photographs over time. Many passionate photographers, despite gathering large collections, later realize they missed the opportunity to create panoramic images that could have been used for decoration or preservation of memories. However, organizing these unstructured collections manually to form panoramas is a daunting task, especially when the sequence and relation between images are unclear.

This project addresses the challenge by introducing an automated solution that organizes and stitches images without requiring manual input. As illustrated in Figure 1, the system flow enables the automatic grouping of related images into separate panoramas, greatly simplifying the process for users with little or no technical background.

Automating such tasks is essential in the evolving field of image processing, where user- friendly, intelligent solutions are increasingly expected. By using a combination of machine learning and computer vision techniques, this project removes the dependency on manual sorting, making the creation of panoramas more accessible and efficient for everyone.

The system first constructs an image database by gathering photographs from various locations. It then detects SIFT keypoints for each image and finds matches across the dataset. An automated clustering algorithm is utilized to group visually similar images, allowing each set to be stitched into a cohesive panoramic image.

**MOTIVATION**

The growing accessibility of digital photography has resulted in people capturing thousands of images across different locations and events. However, despite the abundance of photographs, there is often a lack of structured organization, which makes it challenging to retrieve and utilize these images effectively. One of the most beautiful ways to represent a place or experience is through panoramic photography, where multiple overlapping images are stitched together to create a wide, immersive view. Traditionally, creating panoramas required careful planning during the photography phase and manual efforts afterward to align and merge images. This process is time-consuming, requires technical expertise, and often becomes impractical when dealing with large, unordered image collections.

The motivation behind this project stems from the need to simplify and automate the panorama creation process. As modern applications increasingly aim for user-friendliness and minimal manual intervention, there is a growing demand for intelligent systems capable of understanding and processing visual data autonomously. By leveraging advancements in machine learning and computer vision, it is now possible to automate the organization and stitching of images based on their content, without needing manual sorting or prior knowledge of their relationships.

Moreover, panorama stitching has real-world applications beyond personal use — it is critical in fields like virtual tours, real estate showcasing, geographical mapping, cultural preservation, and immersive media experiences. As industries adopt immersive technologies like VR and AR, the ability to quickly generate panoramic content becomes even more important. Providing an efficient and automated solution for panorama creation can thus save time, reduce errors, and enhance creative possibilities.

**PROBLEM STATEMENT**

In the modern digital age, individuals capture large collections of photographs across various events and locations. However, these images often remain unorganized, making it difficult to identify related photos that could be stitched into panoramas. Traditional panorama creation requires manual sorting, precise alignment, and technical expertise, which is time-consuming and impractical for most users.availability instruction and retail is compelled by these imperatives creating a solid context-aware chatbot that Existing systems generally assume ordered inputs and fail when images vary in scale, orientation, or illumination. There is a strong need for an automated solution that can intelligently group related images and seamlessly stitch them together without requiring manual intervention. This project aims to solve this problem by using machine learning and computer vision techniques, offering an efficient and user-friendly approach to automatic panorama generation.

**SCOPE AND OBJECTIVE**

**Scope:**

This project aims to design and implement a fully automated system for image stitching using machine learning and computer vision techniques. The system accepts a set of unordered input images, processes them to detect common features, and outputs a seamless panoramic image. Traditional stitching methods often require manual image sorting, alignment, or rely on limited transformation handling. In contrast, this project removes the need for manual intervention by introducing automation at multiple stages— image grouping, alignment, warping, and blending.

The proposed system leverages SIFT (Scale-Invariant Feature Transform) for robust feature detection across images regardless of scale, rotation, or lighting differences. It uses RANSAC (Random Sample Consensus) for estimating accurate homography matrices, filtering out mismatches and outliers during feature matching. The scope also includes the use of clustering algorithms to automatically group related images into panoramas, reducing human effort and enhancing scalability.

In addition, this system incorporates image warping and blending techniques to ensure a visually coherent and artifact-free panoramic output. While the current implementation is based on classical computer vision algorithms, the project lays the groundwork for future enhancements using deep learning techniques such as CNN-based feature matching, attention mechanisms, and transformer models, which can handle more complex, real-world scenarios such as low-texture environments, motion blur, and occlusion.

The system is designed to be modular and scalable, making it adaptable for applications such as tourism photography, surveillance, drone imagery, and mobile applications that require high-quality panoramic image generation from unordered image collections.

**Objectives:**

**1. Automate Image Sorting:**

A system is designed to automatically organize images into distinct panorama groups by analyzing matched key points and visual similarities.

**2. Robust Feature Matching:**

The approach employs the Scale-Invariant Feature Transform (SIFT) to detect and match features that remain robust under variations in scale, orientation, and lighting conditions

**3. Homography:**

Apply RANSAC algorithms to compute accurate homography matrices that align overlapping images while handling outliers effectively.

**4. Clustering:**

Implement a clustering strategy that identifies strongly connected groups of images, ensuring that each panorama is created from only the relevant images

**5. Interface:**

A simple web-based GUI will be provided to allow users to upload images and generate

## II. LITERATURE SURVEY

**Automatic Panoramic Image Stitching using Invariant Features**

**Authors: Brown, M. and Lowe, D.**

This work approaches panorama creation as a multi-image matching problem. The authors utilize invariant local features to match images regardless of their order, orientation, scale, or illumination. Their method can also handle noisy datasets by filtering out unrelated images, and it is capable of identifying multiple panoramas within an unordered image collection. Key contributions include techniques like gain compensation and automatic straightening to enhance the final panoramic output.

**Rectangling Panoramic Images via Warping**

**Authors: He, K., Chang, H., and Sun, J.**

In this research, a content-aware warping algorithm is proposed to reshape stitched panoramic images into a rectangular form without noticeable distortions. The process consists of two main steps: a preliminary mesh-free warping stage, followed by a global optimization step using a mesh grid to maintain the structure and straight lines. The results demonstrate that the generated panoramas appear natural and retain visual coherence even after rectangling.

**Implementation of HDR Panorama Stitching Algorithm**

**Author: Ostiak, P.**

Ostiak’s work focuses on adapting the SIFT algorithm for HDR (High Dynamic Range) images. The approach involves using perspective transformations and luminance normalization to improve seam removal between images. This method also improves color consistency across image boundaries, contributing to smoother blending and enhancing the quality of HDR panoramic results.

**Fast Panorama Stitching for High-Quality Panoramic Images on Mobile Phones Authors: Xiong, Y., and Pulli, K.**

Additionally, this research introduces a fast and lightweight panorama stitching method optimized for high-quality performance on mobile devices.. The method incorporates dynamic programming for finding optimal seams, color correction for balancing luminance and color consistency, and blending to smooth transitions. The proposed technique achieves a balance between computational efficiency and image quality, making it particularly suitable for mobile and low-memory environments.

**Image Alignment and Stitching: A Tutorial Author: Szeliski, R.**

Szeliski's tutorial provides a comprehensive overview of the principles behind image alignment and stitching. The paper covers different types of image registration methods, including feature-based and direct pixel-based approaches. Techniques for computing transformations, optimizing alignments, and blending images seamlessly are discussed in depth. The tutorial also addresses common problems like parallax errors and exposure differences, offering solutions such as multiband blending and image warping to enhance the quality of panoramas

## EXISTING SYSTEM

**Description:**

The existing panorama stitching systems primarily rely on manual or semi-automatic approaches, where users are responsible for organizing the images before stitching them. These systems utilize feature detection algorithms such as SIFT (Scale-Invariant Feature Transform), SURF (Speeded-Up Robust Features), and ORB (Oriented FAST and Rotated BRIEF) to identify corresponding points or keypoints across overlapping images. Once keypoints are identified, a transformation, typically homography, is applied to align the images. Following alignment, a blending technique is used to merge the images into a seamless panorama. While this process works well under controlled conditions where images are taken sequentially and are closely related, it requires considerable user input to ensure accuracy. Some popular software tools that rely on this approach include Hugin, Photoshop, and certain mobile applications. These tools typically automate some parts of the stitching process but still require that the images be carefully prepared in advance. The process generally involves capturing images sequentially and ensuring they overlap in a way that makes keypoint detection reliable.

**Disadvantages:**

1. Manual Organization of Images: Existing systems typically require users to pre- organize images in a specific order (e.g., sequential shots), which is not always practical, especially in dynamic environments.
2. Poor Performance with Unordered Datasets: The system struggles when presented with unordered or unrelated images, often failing to correctly identify which images should be stitched together.
3. User Intervention for Error Correction: When keypoints are not matched correctly, or misalignments occur, users must manually adjust parameters or make corrections, which requires technical knowledge.
4. Sensitivity to Environmental Changes: Existing systems are highly sensitive to variations in lighting, scale, and perspective, which can lead to mismatches and visual artifacts.
5. High Likelihood of Artifacts: Problems like ghosting, visible seams, or misalignment often appear, particularly when there are significant differences in exposure or perspective between images.

## PROPOSED SYSTEM

The proposed system aims to develop an automated and efficient image stitching framework using machine learning and computer vision techniques. Unlike traditional stitching methods that require manual image selection and alignment, this system automatically detects, matches, and stitches images into a seamless panoramic view. The approach leverages Scale-Invariant Feature Transform

(SIFT) for feature extraction, RANSAC (Random Sample Consensus) for homography estimation, and clustering algorithms to group related images dynamically.

**Key Features of the Proposed System:**

1. Automated Image Grouping: Traditional systems require users to manually organize images, which is time-consuming and error-prone. The proposed system addresses this limitation by utilizing clustering algorithms that automatically group images based on feature similarity. This enables the system to automatically detect which images belong to the same panorama, eliminating the need for manual image selection. This is particularly useful when dealing with unordered or mixed datasets where images may be captured under different conditions or from different sources.
2. Feature-Based Keypoint Detection: Rather than relying on predefined reference points or assumptions about the image layout, the system uses SIFT to detect distinctive keypoints across all images. SIFT is robust against variations in scale, rotation, and illumination, making it more adaptable to images captured in diverse environments. The keypoints are used to find matching features between images, ensuring that the correct points are identified even if the images are taken from different angles or perspectives.
3. Homography Estimation with RANSAC: To align images accurately, the system employs RANSAC, a robust algorithm used to estimate homographies while rejecting outliers. RANSAC is particularly effective when the keypoint matches are noisy or incomplete, which is common in real-world images. By applying RANSAC, the system can more reliably estimate the transformation between images and align them correctly, even in challenging scenarios.
4. Dynamic Image Stitching: After aligning the images, the system uses an advanced stitching algorithm to seamlessly merge the images into a single panoramic view. Unlike traditional methods that might require manual adjustment of blending parameters, the proposed system adapts automatically to different lighting conditions, image content, and perspective changes. It applies optimized blending techniques to ensure a smooth transition between images, minimizing visible seams and ghosting effects, which are common in traditional panorama stitching systems.
5. End-to-End Automation: The proposed system is designed to operate autonomously, from detecting and grouping related images to generating the final stitched panorama. This eliminates the need for user intervention in most stages of the process. In contrast, existing systems often require users to manually select images, fine-tune parameters, and adjust alignment errors.

**Advantages of the Proposed System:**

1. Fully Automated Process: Users no longer need to manually select or organize images. The system automatically detects, groups, and aligns images, significantly reducing the complexity of panorama stitching.
2. Handling Unordered Datasets: Unlike traditional systems that require images to be sequential or properly organized, the proposed system can handle unordered or mixed images, making it more versatile.
3. Robust and Accurate: The use of SIFT for keypoint detection and RANSAC for homography estimation ensures more accurate and reliable image alignment, even in the presence of noise or mismatches.
4. Real-Time Stitching: The system's performance is optimized for real-time stitching on mobile and low-resource devices, making it practical for everyday use and on-the-go applications.
5. Seamless and Artifact-Free Results: Advanced blending techniques minimize visual artifacts such as seams and ghosting, producing a smooth and high-quality panorama.

Adaptability to Various Conditions: The system can adapt to changes in lighting, scale, and perspective, ensuring that it can be used in diverse environments, from indoor settings to outdoor landscapes

## III. MODULE DESCRIPTION

The system is divided into multiple interdependent modules, each responsible for a specific function in the process of automatic image stitching. These modules work together to ensure a seamless and automated experience from input to panorama generation.

1. Image Database Preparation: This module acts as the first point of interaction between the user and the system. Its primary function is to receive and organize a set of images for stitching. Users can upload unordered images in formats such as JPEG or PNG. Once uploaded, the images are stored in a working directory or temporary database. Preprocessing steps are executed here to ensure uniformity, including resizing all images to a standard dimension, adjusting resolution if necessary, and converting incompatible file types to supported ones. These steps help reduce discrepancies in image size and format, which can otherwise affect the performance of subsequent modules. By cleaning and standardizing the dataset, this module ensures that all input images are suitable for reliable feature extraction and comparison in the next phases of the pipeline.
2. Feature Detection and Extraction Module : Once images are prepared, the next step involves identifying unique features within each image. This module utilizes the Scale-Invariant Feature Transform (SIFT) algorithm to detect keypoints that represent stable elements such as edges, corners, and textures. These keypoints are not affected by variations in scale, rotation, or brightness, making them ideal for image matching. For every keypoint, a descriptor is generated—typically a high-dimensional vector that captures the visual context around that point. These descriptors form the foundation for comparing features across images. By systematically analyzing the entire dataset, this module creates a structured set of descriptors for each image, which are then passed to the matching module. Its performance directly influences the accuracy of identifying overlapping regions in later stages.
3. Feature Matching Module : This module is responsible for comparing the descriptors extracted from each image to those of every other image in the dataset. Using a nearest-neighbor search strategy, the system attempts to find the most similar descriptor pairs between images. To ensure that only the most reliable matches are retained, Lowe's ratio test is applied. This test compares the distance of the best match to the second-best and accepts the match only if the ratio is below a certain threshold,which helps eliminate ambiguous or incorrect matches. The result is a filtered set of high-confidence correspondences between images. These matches form the basis for identifying overlapping images, which will be aligned and stitched together. The accuracy and robustness of this module are critical because poor matching can lead to incorrect alignments and visible artifacts in the final panorama.
4. Homography Calculation Module: Once feature correspondences are identified, the next step is to determine the geometric relationship between overlapping images. This module computes a homography matrix for each image pair using the RANSAC (Random Sample Consensus) algorithm. The homography matrix defines how one image should be warped to align accurately with another. RANSAC enhances the reliability of this process by discarding mismatched points (outliers) and considering only consistent feature pairs (inliers) for transformation calculation. Multiple iterations are run to find the transformation with the highest inlier count. This ensures that even if some points are noisy or incorrect, the final transformation remains robust. The computed matrices are later used for image warping and positioning during the stitching process. Without this step, proper alignment of the images would not be possible.
5. Image Clustering Module: In many real-world scenarios, users may upload a mixed set of images, some of which belong to different scenes or trips. This module handles such scenarios by organizing the dataset into logical groups or clusters. It treats each image as a node in a graph, and uses the results from the matching and homography steps to define edges between them. If two images have sufficient matches and a valid homography, an edge is created. The graph is then analyzed to find strongly connected components, which are considered individual clusters. Each

cluster represents a set of images likely to form a single panorama. This approach allows the system to process multiple panoramas in one batch without manual sorting. It increases automation and ensures that only related images are stitched together, reducing the chance of incorrect combinations.

## IV. SYSTEM DESIGN

**SYSTEM ARCHITECTURE**

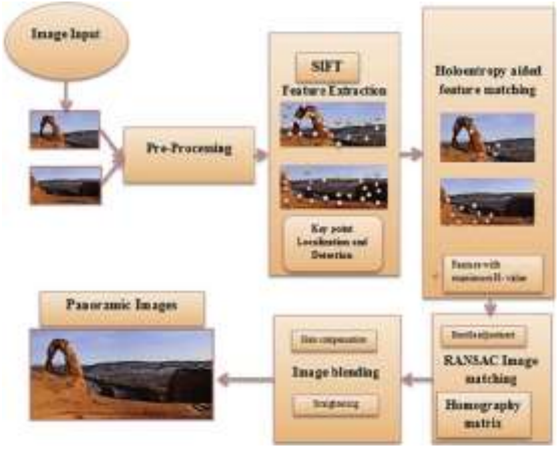


Fig. System Architecture

## V. OUTPUT SCREENS


Fig: web page interface

Fig: Image Upload and Selection Dialog

Fig: Final Stitched Panorama Output

## VI. CONCLUSION

This project successfully developed an automated system for image stitching using machine learning and computer vision techniques. By utilizing algorithms such as SIFT for feature detection, RANSAC for homography estimation, and clustering for image grouping, the system efficiently organizes unstructured image datasets and creates seamless panoramic outputs without manual intervention. The approach proved to be robust against variations in scale, orientation, and lighting, and was able to automatically identify and stitch related images even from unordered collections. Through extensive testing, the system demonstrated high reliability, accuracy, and performance across different environments. Although minor challenges such as cluttered scenes and low-quality images were observed, the system overall meets its objectives and offers significant potential for applications in fields like tourism, real estate, virtual tours, and personal photography. Future improvements could further enhance its capabilities by incorporating advanced matching techniques or deep learning models.

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