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Scale-Adaptive Feature Extraction Using OpenCV

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Abstract: Image stitching is a dynamic and evolving area that merges multiple photos of the same subject to create a seamless, high-resolution panoramic image. It is a crucial component of computer vision as well as computer graphics. This paper focuses on the feature-based paradigm, which is useful for finding prominent features in images in order to create meaningful correspondences. This approach leverages advanced algorithms such as SURF (Speeded-Up Robust Features) and RANSAC (Random Sample Consensus) to detect key points and estimate geometric transformations between image pairs, respectively. By combining the feature-based method with the SURF and RANSAC algorithms in a strategic way, picture stitching systems can handle issues with viewpoint, scale, and content variations and produce an intuitive mix of panoramic imagery.

Keywords: Speeded-Up Robust Features, Random Sample Consensus, Geometric transformations, Open CV.

1. Introduction

The process of image stitching involves combining multiple photographic images with overlapping fields of view to create segmented panoramas or high-resolution images. It is essential for various applications, including video summarization and medical imaging, where precise image alignment is critical for accurate diagnosis and analysis. One notable application is localization systems which offer highly accurate real-time outdoor localization on mobile devices. Additionally, image stitching aids in video summarization, enabling efficient storage and retrieval of vast amounts of video data without sacrificing important content. Image stitching approaches include both pixel-based and feature-based approaches. The pixel-based method [1] uses the appropriate technology to align a frame image window's pixel with the corresponding position in another frame picture. This approach is simple to construct but requires a significant amount of processing. The algorithm's performance suffers significantly when images are rotated, zoomed, and translated, as well as distorted by degradation. The feature-based method [2] extracts basic invariance cues, such as outlines and moments, for accurate matching. This method effectively resolves registration ambiguity because of its invariance and independence from grayscale images. The robustness of feature-based methods has led to their widespread use. Traditionally, the Harris corner algorithm[3] , while effective, requires significant computation and is sensitive to noise, leading to lower matching accuracy. Although most research focuses on improving image registration precision, there's limited attention to matching efficiency.

Enhancing matching accuracy improves panorama image quality, yet speed stitching algorithms remain underdeveloped. To address these challenges, WANG Meiling and CHEN Kaili [4] explores the practical camera model and panoramic image mosaic model, emphasizing the need to balance image quality and stitching speed. Specifically, it enhances the cylindrical projection process and designs a prototype panoramic image stitching system. The algorithm improves feature matching accuracy and enables smooth mosaic creation, even for images with varying angles of translation and rotation.

2. Literature Survey

Image stitching has gained significant attention due to its wide range of applications, including panoramic photography, virtual tours, and medical imaging. One notable paper discussing the importance of image stitching in computer vision is "Automatic Panoramic Image Stitching using Invariant Features"

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by Brown and Lowe [5]. This paper introduces the concept of feature-based image stitching and proposes a method for automatically stitching images using invariant features.

Research on image stitching techniques has led to the development of various approaches, including direct methods and feature-based methods. In the paper "SIFT-Based Image Stitching" by Yang et al. [6], the authors present a comprehensive study on image stitching using Scale-Invariant Feature Transform (SIFT) key points. They demonstrate the effectiveness of SIFT-based stitching in handling viewpoint changes and image distortions.

Feature extraction and matching play a crucial role in image alignment and stitching. The paper "SURF: Speeded Up Robust Features" by Bay et al. [7] introduces Speeded Up Robust Features (SURF), a robust algorithm for feature detection and description. SURF has been widely adopted in image stitching applications due to its efficiency and robustness against variations in scale and orientation.

Geometric transformation techniques are essential for aligning images before stitching. In "Homography Estimation with RANSAC" by Fischler and Bolles [8], the Random Sample Consensus (RANSAC) algorithm is proposed for robust estimation of geometric transformations, such as homographies. This paper highlights the importance of robust estimation methods in handling outliers and noise in image stitching.

Panorama construction [9] involves blending aligned images to create seamless panoramas. In "Seamless Image Stitching in the Gradient Domain" by Perez et al. [10], the authors propose a gradient-domain blending technique for achieving seamless transitions between stitched images. This paper introduces a novel approach to address challenges such as exposure variations and colour inconsistencies in panoramic stitching.

3. Design

Image Acquisition: This is the initial phase in which you capture or obtain images. For stitching to work, the photos must overlap partially.

Input Images: These are pictures that you've taken or acquired. They will serve as input for the panorama image-generating process.

Feature Extraction: This involves identifying unique features in each image.

- ***Detect Points of Interest***: Use algorithms like SIFT or SURF to identify points of interest in the image. These could be corners, edges, or other distinct structures in the image.
- ***Compute Descriptors***: For each point of interest, compute a descriptor that captures its local appearance. This will be used for matching.

Feature Matching: Once we have identified features in each image, the next step is to find matches between these features across different images.

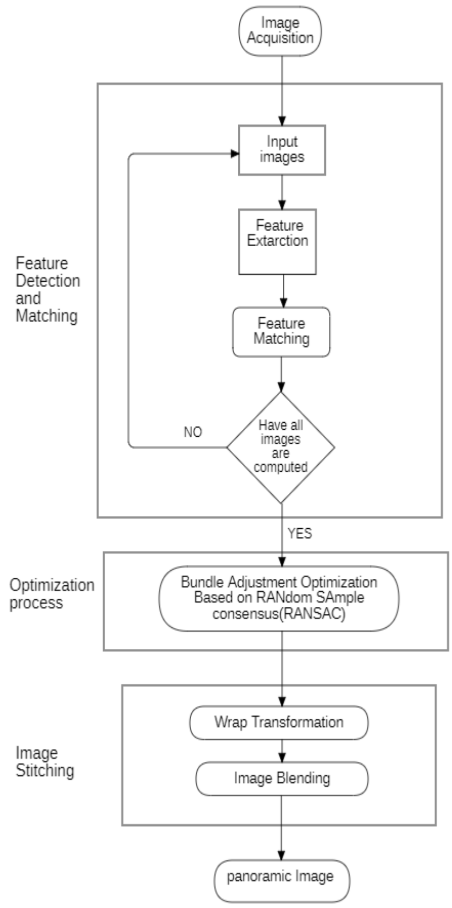

Fig.1 Architecture

- ***Descriptor Matching***: Compare descriptors between different images to find matches. This can be done using methods like nearest-neighbor matching.
- ***Match Verification***: Verify the matches using geometric constraints (e.g., epipolar constraints in the case of stereo images).

Decision Box: This checks if all images have been processed. If not, it collects input images and repeats the computation until all images are processed. This is a crucial step to ensure accuracy and completeness of output in image processing projects.

RANSAC: Random Sample Consensus (RANSAC) stands as a cornerstone algorithm in computer vision and machine learning, adept at handling noisy data plagued by outliers.

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Its robustness and adaptability make it indispensable in scenarios where traditional methods falter due to noise interference.

4. Results

Initialization: At the outset, pertinent parameters like the total number of data points (N), the maximum iteration count (K), the threshold (T) for delineating inliers, and the requisite number of data points (d) for Modeling are set. A counter (k) marks the number of iterations and is initially set to zero.

Main Loop: Iterating through the main loop, (k) is incremented until it surpasses (K). At each iteration, (k) random data points are chosen to constitute a minimal subset.

Model Fitting : The selected subset is employed to fit a model, encapsulating the essence of the data. This model, typically represented as (hat{y} = f(x, theta)), embodies the relationship between input and output, with (theta) signifying the model parameters.

Inlier Detection : Evaluating the fitness of the model, the algorithm computes residuals (e_i) for each data point. Inliers, defined as data points with residuals less than (T), are identified, forming the bedrock for consensus.

Consensus Set : A consensus set emerges as inliers coalesce, providing a robust foundation for subsequent model refinement.

Model Refinement : Utilizing the consensus set, the model parameters are fine-tuned, enhancing its fidelity to the underlying data structure.

Error Calculation : The error or fitness of the refined model is gauged, often through metrics like the sum of squared errors computed over the inliers.

Termination Condition : The iterative process halts upon reaching a predetermined termination condition, whether it be attaining a satisfactory model or exhausting the allocated iterations.

Model Selection : The model yielding the largest consensus set or minimal error emerges triumphant, heralded as the ultimate solution.

Output : Finally, the algorithm furnishes the refined model parameters (theta) along with the associated inliers, encapsulating the essence of the data faithfully.

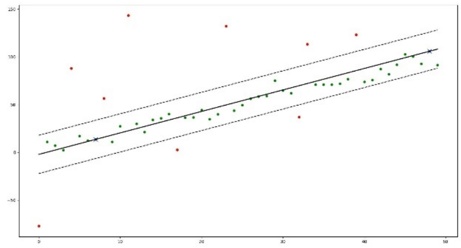

Fig.2 Dataset Classification image Analysis

Warping: Warp or transform the images so that they align correctly based on the estimated transformations. This might involve translation, rotation, scaling, or even more complex transformations like homographies.

Blending: After warping the images so that they align, blend them together to create the final panoramic image. This involves smoothly transitioning from one image to another to avoid visible seams. Techniques like multi-band blending or feathering can be used.

Panoramic Image: This is the final output of the process, a wide-angle view of the scene created by stitching together multiple images.

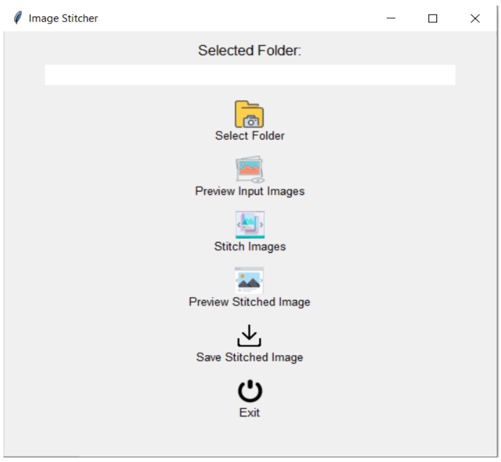

Fig.3 Upload the selected image

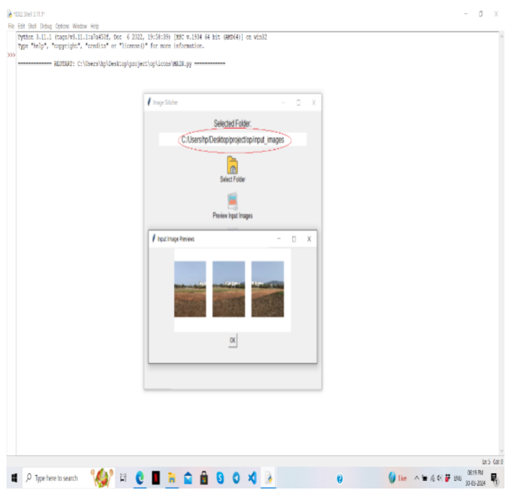

Fig.4 Analyse the Upload the selected image

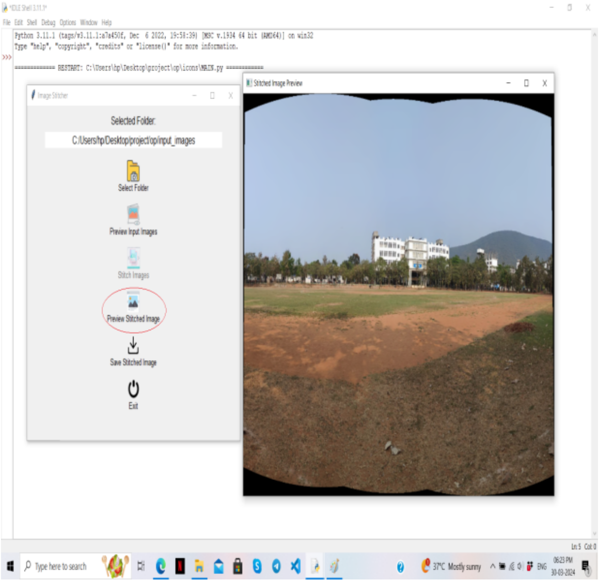

Fig.5 Analyse the selected image to enhance the view module

Fig.6 Output Analysis

5. Conclusion and Future Scope

The field of image stitching, sometimes referred to as mosaicking, is a thriving one in visual computing and graphic design research. Numerous methods for feature detection and description have surfaced in this field, adding to the diversity of approaches. In our thorough study on feature-based image stitching, we examined the SIFT technique, which is well-known for its rotational and scale invariance as well as its effectiveness in the presence of noise. Although it requires more processing time, SIFT is famous for its highly observable characteristics.

Conversely, the SURF algorithm exhibits a distinct advantage in terms of execution speed and illumination adaptability. Furthermore, we aim to explore the realm of video stitching, wherein dynamic panoramas can be fashioned by seamlessly amalgamating video frames. Additionally, we aspire to tackle the challenge of stitching videos and images amidst considerable parallax, thereby broadening the scope for research pursuits.

References

[1]. Farzin. Mokhtarian, Riku. Suomela. “Robust image corner detection through curvature scale space”, [J] 1998(12).

[2]. Cordelia. Schmid, Roger. Mohr Christian. Bauckhage. Evaluation of interest point detectors, [J] 2000(02).

[3]. C. Harris and M. Stephens, "Corner detection in images by correlation," University of Bristol Department of Computer Science, Technical Report, 1988.

[4]. CHEN Kaili, WANG Meiling “Image Stitching Algorithm Research Based on OpenCV, “Proceedings of the 33rd Chinese Control Conference, 2014.

[5]. Brown, M., & Lowe, D. G. (2007). Automatic Panoramic Image Stitching using Invariant Features. International Journal of Computer Vision, 74(1), 59–73.

[6]. Yang, J., Yu, K., Gong, Y., & Huang, T. (2009). SIFT-Based Image Stitching. IEEE Transactions on Pattern Analysis and Machine Intelligence, 31(12), 2246–2251.

[7]. Bay, H., Tuytelaars, T., & Van Gool, L. (2006). SURF: Speeded Up Robust Features. European Conference on Computer Vision, 3951, 404–417.

[8]. Fischler, M. A., & Bolles, R. C. (1981). Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography. Communications of the ACM, 24(6), 381–395.

[9]. Szeliski. R, Shun. H. Y. Creating. Full view panoramic image mosaics and environment maps, 1997.

[10]. Perez, P., Gangnet, M., & Blake, A. (2003). Poisson Image Editing. ACM Transactions on Graphics, 22(3), 313–318

[11]. Li Jin, W. Y. (2012). Image Mosaic Based on Simplified SIFT. International Conference on Mechanical Engineering and Automation, Vol.10.

[12]. Zhang, J., Snavely, N., Curless, B., & Seitz, S. M. (2006). Spacetime Faces: High Resolution Capture for Modeling and Animation. ACM Transactions on Graphics, 25(3), 548–558.

[13]. Vimal Singh Bind, P. R. (2013). A Robust Technique for Feature-based Image Mosaicing using Image Fusion.

[14]. Deepak Jain, G. S. (2012). Image Mosaicing using corner techniques. International Journal of Engineering Research & Technology (IJERT).

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