

A Comparative Analysis Review on Panoramic Image Stitching Algorithms with Presence of Gaussian Noise

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Abstract

Panoramic image stitching is a cornerstone of modern computer vision, yet its performance degrades significantly under noisy conditions particularly Additive White Gaussian Noise (AWGN). This study presents a comprehensive theoretical analysis of the robustness of three widely used feature extraction and description algorithms SIFT, SURF, and ORB in the presence of AWGN. Focusing on their behavior during feature detection, description, matching, and geometric verification. These three methods were evaluated based on three critical criteria: noise resilience, computational efficiency, and matching accuracy. The analysis reveals that SIFT demonstrates the highest theoretical robustness to Gaussian noise due to its multi-scale Difference-of-Gaussians (DoG) framework and gradient-based descriptors, which inherently suppress high-frequency noise. However, this robustness comes at the cost of high computational complexity, rendering it unsuitable for real-time applications. Conversely, ORB offers exceptional speed through binary descriptors and the FAST detector but exhibits marked sensitivity to intensity perturbations caused by AWGN, leading to significant performance degradation in noisy environments. SURF emerges as the optimal compromise: leveraging integral images, it achieves near-SIFT-level robustness while maintaining significantly lower computational demands. Research underscores the importance of the Fast Library for Approximate Nearest Neighbors (FLANN) library in enhancing feature matching and the Random Sample Consensus (RANSAC) algorithm, offering a methodological framework for choosing the appropriate algorithm in panoramic compositing systems. It emphasizes balancing noise characteristics, speed, and accuracy requirements.

Keywords: Image Stitching, Gaussian noise, Panoramic Image, Feature Descriptor, SIFT, SURF, ORB, FLANN, RANSAC

المخلص

يُعد تركيب الصور البانورامية (Panoramic Image Stitching) ركيزة أساسية في الرؤية الحاسوبية الحديثة، إلا أن أدائه يتدهور بشكل ملحوظ تحت ظروف الضوضاء، وخاصة الضوضاء الغاوسية البيضاء المضافة (AWGN). يقدم هذا البحث تحليلاً نظرياً شاملاً لمتانة ثلاث خوارزميات شائعة لاستخلاص ووصف المعالم SIFT و SURF و ORB في وجود الضوضاء الغاوسية. مع التركيز على سلوكها خلال مراحل اكتشاف المعالم، ووصفها، ومطابقتها، والتحقق الهندسي. تم تقييم هذه الخوارزميات بناءً على ثلاثة معايير حاسمة: مقاومة الضوضاء، الكفاءة الحسابية، ودقة المطابقة. أظهر تحليل الدراسة أن خوارزمية SIFT تتمتع بأعلى متانة نظرية ضد الضوضاء الغاوسية، وذلك بفضل إطار عملها متعدد المقاييس القائم على فرق الغاوس (DoG) ومُوصفات المعتمدة على التدرج (Gradient-based descriptors)، والتي تعمل بطبيعتها على قمع الضوضاء عالية التردد. ومع ذلك، فإن هذه المتانة تأتي على حساب تكلفة حسابية عالية تجعلها غير مناسبة للتطبيقات التي تتطلب استجابة فورية. في المقابل، توفر خوارزمية ORB سرعة استثنائية عبر مُوصفات الثنائية وكاشف FAST، لكنها تُظهر حساسية واضحة للاضطرابات في شدة البكسل الناتجة عن الضوضاء الغاوسية، مما يؤدي إلى تدهور كبير في الأداء في البيئات الصاخبة. وتبرز SURF كأفضل حل وسط: فهي تحقق متانة

تقترب من مستوى SIFT باستخدام صور التكامل (Integral Images) مع الحفاظ على متطلبات حسابية أقل بكثير. تؤكد الأبحاث على أهمية مكتبة سريعة للجيران الأقرب التقريبيين (FLANN) في تحسين مطابقة الميزات وخوارزمية إجماع العينة العشوائية (RANSAC)، مما يوفر إطارًا منهجيًا لاختيار الخوارزمية المناسبة في أنظمة التركيب البانورامي. كما تُشدد على تحقيق التوازن بين خصائص الضوضاء والسرعة ومتطلبات الدقة.

الكلمات المفتاحية: تركيب الصور، الضوضاء الغاوسية، الصورة البانورامية، SIFT، FLANN، RANSAC

1. Introduction

Panoramic image stitching is an essential technique in computer vision and image processing. A panoramic image is constructed by multiple images into one wide-angle image. It is applied in various fields like virtual reality, autonomous robots, remote sensing, and medical imaging [1-2]. Image stitching methods generally consist of two main phases: the first phase is image alignment and the second is image blending. The image alignment operation finds and matches feature points between images. to which points used within the process are really important for detecting the quality and computational time [3]. Images are usually exposed to many types of noise, the most is Additive White Gaussian Noise (AWGN). Such noise reduces the steadiness of keypoint detection and the consistency of feature descriptors, both of which are important for panoramic image stitching accuracy[4-5].

While many studies have evaluated feature extraction algorithms in noisy environments, there is still a lack of a combined theoretical basis that compares the noise resistance of SIFT, SURF, and ORB algorithms based on their mathematical concepts. Differences in experimental settings often lead to conflicting results, highlighting the need for a clear theoretical analysis that identifies the strengths and weaknesses of each algorithm when subjected to noise. This paper is organized as follows: Section 1 discusses the introduction. Section 2 defines the study's scope and objectives. Section 3 describes the theoretical basis of Gaussian noise, Section 4 conducts a comparative analysis of the noise resilience of three prominent feature extraction algorithms: SIFT, SURF, and ORB, examining their mathematical frameworks and sensitivity to additive white Gaussian noise. Section 5 surveys the related literature on panoramic image stitching and evaluates the robustness of feature descriptors under various degradations. Section 6 shows the theoretical performance of the findings, based on robustness, accuracy, and computational efficiency. Lastly, Section 7 concludes the paper by summarizing the key insights and proposing future research directions, particularly focusing on the development of noise-resilient.

2. Scope and Objective

The proposed study created a theoretical comparison based on the performance of SIFT, SURF, and ORB algorithms on images impacted by Gaussian noise, aiming to determine which algorithm is most effective in detecting stable and reliable keypoints. Building upon prior research in image processing and computer vision using these algorithms, this analysis examines the precision of extracted features through various test methods. The findings will provide valuable insights and serve as a foundation for future research in this area.

3. Gaussian Noise Principle

Noise relates to statistical alteration whose probability density function follows a normal distribution. It commonly degrades image quality and hinders subsequent processes such as image acquisition, transmission, storage[6], visualization, segmentation and recognition damaging image quality[7-8]. In the panoramic image stitching, Gaussian noise can introduce a distortion that complicates image alignment, obstructs the matching of overlying regions, and reduces the visual reliability of the resultant panorama. The theoretical Gaussian noise model may be stated as shown in the equation (1) [8]:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad \dots\dots 1$$

where parameters x and y define pixel coordinates, and σ describes the spread of the noise. This formula provides a mathematical type of the noise distribution without indicating any filtering or denoising process. Figure 1 shows an original image with a corrupted image due to this noise.



Figure 1. Grayscale image (a) Original Image (b) The Corrupted Image by Additive Gaussian Noise [9].

4. Overview of Feature Descriptors and Noise Resilience

The following provides a brief introduction to the three feature extraction algorithms analyzed in this study: SIFT, SURF, and ORB.

4.1 SIFT (Scale-Invariant Feature Transform)

- A feature extraction method in computer vision and image processing is SIFT (Scale-Invariant Feature Transform). Illustrious for its performance against variations in scale, rotation, lighting, and perspective. This flexibility aids in detecting specific key points, even in degraded environments such as noisy, chaotic, or occluded scenes. The process of detecting key points is separated into two main phases. The first phase involves generating a scale space by repeatedly applying Gaussian filters on the original image to perform scale stability. The image is then resized to half its size, followed by repeated Gaussian smoothing, generating an image pyramid to the original image at the base (level 1) [3]. In the second phase, calculates the Difference of Gaussians (DoG) by subtracting consecutive scales within the pyramid. Keypoints are identified by analyzing the $3 \times 3 \times 3$ neighborhood around each pixel, selecting pixels that exhibit extrema (either maximum or minimum) in DoG values as key points. Once keypoints are noticed, the feature descriptor algorithm computes them. These descriptors, dependent on location histograms that seize the local slope directions of the keypoint neighborhood, present a complete illustration of the adjacent features. These comprehensive features make SIFT very efficient for precise feature matching and recognition tasks [4][10].

4.2 SURF (Speeded-Up Robust Features)

The advance of digital image processing in the field of feature extraction led to the emergence of SURF (Speeded-Up Robust Features) and became a substitute for SIFT (Scale-Invariant Feature Transform). The SURF algorithm was discovered by Bay et al. in 2006 to overcome the limitations of other feature descriptors such as SIFT. The descriptor is designed with scale and rotational constancy, allowing for the identification of scaled features in another image [10]. SURF strives to achieve high efficiency and resilience to image transformations, making it ideal for real-time applications and large-scale visual database systems. This algorithm is classified into three main steps: the first step is interest point detection, the second is the orientation task, and the last is feature description. These steps are connected and cooperative extract distinctive and identifiable features from an input image [11][12]. Scale-space extrema are recognized by constructing a difference-of-Gaussian (DoG) pyramid, which is formed by subtracting neighbor levels of the Gaussian pyramid. Then, to detect extrema a comparison between neighbor pixels within similar scales and across adjacent scales is performed. The representation of this process is shown in equation (2)[12]:

$$\text{DoG}(x, y, \sigma) = G(x, y, k\sigma) - G(x, y, \sigma) \quad \dots\dots (2)$$

where $\text{DoG}(x, y, \sigma)$ represents the difference-of-Gaussian at coordinates (x, y) and scale σ , and $G(x, y, \sigma)$ is the utilization of the Gaussian response at coordinates (x, y) and scale σ .

4.3 ORB (Oriented FAST and Rotated BRIEF)

ORB (Oriented FAST and Rotated BRIEF) is an important feature detection and description algorithm used in panoramic image stitching. ORB detects and matches attributes between overlying images [3]. ORB detects keypoints in each image using the FAST (Features from Accelerated Segment Test) corner detector, typically fixing prominent corners and edges. These keypoints are then described using Rotated BRIEF, resulting in compact binary descriptors that are invariant to rotation. Then these descriptors are matched crosswise to the overlying images by Hamming distance, because it is highly efficient for dual data. To model the geometric transformation between images, a homography matrix is typically estimated using the RANSAC algorithm based on the matched keypoints. The advantages of the popular use of ORB in panoramic stitching applications make it perfect for real-time applications. Due to this, it is quick computationally.

4.4 Fast Library for Approximate Nearest Neighbors (FLANN) and Random Sample Consensus (RANSAC)

After detecting and describing features, panoramic image stitching involves establishing robust correspondences between keypoints in overlapping images—a step highly susceptible to noise-induced errors. This is accomplished through feature matching, followed by geometric validation. FLANN is a highly optimized library designed to accelerate the computationally intensive task of finding the best descriptor matches. It performs an approximate nearest neighbor (ANN) search in high-dimensional descriptor spaces 128-dimensional SIFT and 64-dimensional SURF. By employing advanced data structures like KD-trees or hierarchical k-means clustering, FLANN avoids the exhaustive, slow search of traditional methods[13]. This efficiency is crucial for maintaining the speed of the overall stitching pipeline, especially in large-scale or real-time applications. To ensure the geometric integrity of the final panorama, the RANSAC (Random Sample Consensus) algorithm is employed as a robust outlier rejection mechanism[14]. RANSAC iteratively estimates the homography matrix the projective transformation required to align the images by:

1. Randomly selecting a minimal subset of matched points.
2. Computing a candidate homography based on this subset.

3.Counting the number of matches (inliers) that agree with this model within a predefined tolerance.

The model with the most inliers is chosen as the final transformation. RANSAC filters out noise, while FLANN aids in fast matching for reliable image stitching.

5. Literature Review

Among the most affected feature detection algorithms are SIFT, SURF and ORB each developed to resolve the compromise between robustness and computational efficiency. These three methods represent the factors in the evolution of feature-based computer vision systems and continue to serve as reference techniques in both academic research and practical implementations. Below is a literature review of these methods:

5.1 SIFT (Scale-Invariant Feature Transform)

Forero et al. [15] confirmed that SIFT, SURF, and ORB show difference in resistance to degradations such as Gaussian noise. SIFT proves its performance in stability with its higher computational cost [8-10]. Similar investigations further confirmed varying levels of robustness to noise and geometric transformations, aligning with the theoretical insights discussed in this work. Yingpeng, C. H. I. & Chang, L. I. U. adapted several works on SIFT for SAR–optical image alignment. Yingpeng and Chang modified SIFT for multi-modal matching, Yu et al. improved robustness to speckle noise and nonlinear grayscale differences using rotation-invariant amplitude descriptors and direction histograms, and Dellinger et al. proposed SAR-SIFT with redefined gradients and the ROEWA operator to effectively handle SAR-specific speckle noise [16]. Similarly, Divya et al. [17] integrated structure tensors into SIFT, increasing correct feature matches and improving overall registration accuracy. Mistry et al. made a comparison between SIFT and SURF, reporting that each algorithm presents good results in different circumstances. For example, SURF is better than SIFT in terms of rotation invariance, blur, and warp transform, while SIFT is better than SURF in terms of scale invariance [18]. A robust image hashing technique is presented, integrating Scale-Invariant Feature Transform (SIFT), Singular Value Decomposition (SVD), and Zernike moments. This combination effectively resists rotation attacks and extracts key features from images, with experimental results showing resilience against various types of attacks[19].

5.2 SURF (Speeded-Up Robust Features)

Makandar A, et al. and Thapar P, et al., analyze several corrupt images with Gaussian, salt-and-pepper, and speckle noise and compare SIFT, SURF, and HOG using the number of correct/valid matches between original and noisy images as the metric [20-21]. SURF is faster with performance close to SIFT, and is often judged the “best compromise” in noisy scenarios. In one experiment, effectiveness (correct matches / detected features) decreased with increasing Gaussian noise, but SURF retained relatively robust matching compared with other algorithms [20]. Ashwani reviews the SURF feature descriptor, noted for its robustness, efficiency, and invariance to image transformations. It explores the principles and components of SURF, as well as its applications in tasks like object recognition, image matching, and 3D reconstruction. The study also examines recent advancements and variations of the SURF algorithm, and compares it with other feature descriptors, aiming to enhance understanding of SURF's importance in computer vision [22]. The proposed research combines SURF with ATSERC, which significantly improves medical image registration accuracy by adapting to scale rotation and illumination variations. They applied Gaussian filters as image preprocessing for image denoising[23]. Joey et. al, suggests advanced changes to

the accuracy and performance of the (SURF) algorithm for ultrasound images via applying many identical measures. These measures include Euclidean distance, cityblock distance, variation, and correlation. Cityblock distance with SURF provides the best results with the highest PSNR and low execution time for SNR [24].

5.3 ORB (Oriented FAST and Rotated BRIEF)

Rublee E. et al., evaluate a visual vocabulary method that utilizes offline clustering to identify exemplars that are uncorrelated and suitable for matching purposes. These techniques may also prove beneficial in discovering uncorrelated binary tests. A system closely related to ORB is [3], which introduces a multi-scale Harris keypoint along with an oriented patch descriptor [25]. Ahmed et. al, presented an object detection and classification framework that integrates feature extraction and optimization techniques. BRIEF and ORB are used for feature representation and object separation, while a genetic algorithm optimizes [26] random forest parameters. The approach achieves strong performance on Corel-1k and MSRC datasets, and detection accuracies of 87.2% and 86.6%. The results demonstrate the effectiveness of GA-based optimization despite some limitations [27]. Akdim K et al. proposed an enhanced feature-based image registration method using ORB combined with a modified RANSAC algorithm. By introducing a Median Absolute Deviation (MAD)-based adaptive threshold, the method overcomes limitations of standard RANSAC such as high computational cost and fixed thresholds. The approach increases inlier accuracy and robustness to noise and distortion, outperforming standard ORB in MSE, NMI, SSIM, and PSNR metrics [28]. Işık M. presents a study of a comprehensive evaluation of traditional feature detectors and descriptors, including SIFT, SURF, ORB, AKAZE, BRIEF, and others, analyzing their efficiency and robustness under various image transformations. Using the large-scale Photo Tourism 2020 dataset, results show that FAST with ORB and a BF matcher provides the fastest performance, ORB performs well under affine and brightness changes, and AKAZE is most robust to blur, distortion, and rotation [29]. Cai et. al, the study examines the impact of image noise on monocular feature-based visual SLAM. A synthetic dataset with varying noise levels is used, and images are denoised using the FFDNet deep learning model. Experimental results show that ORB outperforms SIFT and SURF in correct feature matching under noisy conditions, and image denoising can significantly improve the accuracy of monocular feature-based visual SLAM under certain conditions. This descriptor, designed for image stitching, demonstrates strong rotational and scale invariance [30]. A visual comparison of SIFT, SURF and ORB is shown in Figure 2 and recorded in table 1.

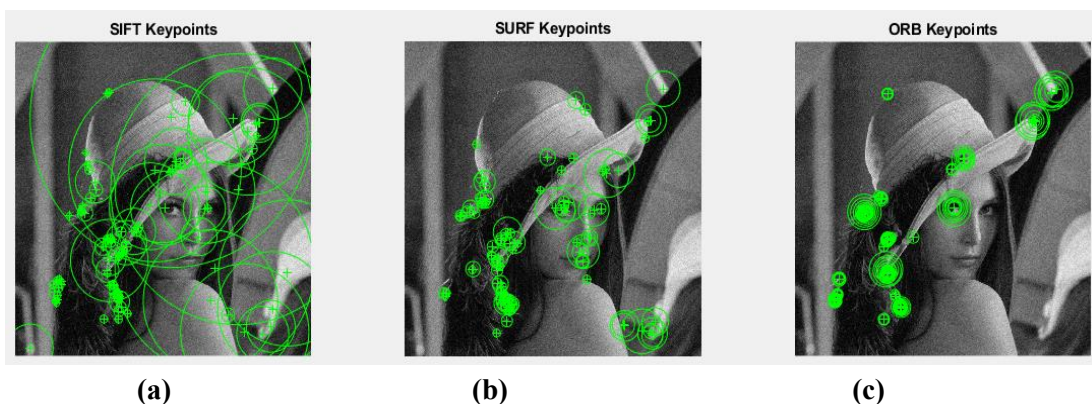


Figure 2. Visual comparison of keypoints Detection Under Gaussian Noise (a) SIFT, (b) SURF and (c) ORB

Table 1: Comparison of Feature Descriptors under Gaussian Noise

Feature Extractor	Descriptor Type	Noise Robustness (Theoretical)	Computational Speed	Primary Mechanism for Noise Tolerance	Advantages	Disadvantages
SIFT	Gradient-based (128-dim)	High	Slowest	Scale-space filtering (DoG) and gradient averaging	Highly robust to scale, rotation, and noise.	High computational cost, slow for real-time.
SURF	Haar Wavelet-based (64/128-dim)	Moderate	Fast	Integral images and box filters for fast approximation	Faster than SIFT, good balance of speed and robustness.	Less distinctive than SIFT, moderate noise sensitivity.
ORB	Binary (256-bit)	Low	Fastest	FAST corner detector and binary BRIEF descriptor (highly intensity-sensitive)	Extremely fast, suitable for real-time applications.	Highly sensitive to noise and intensity changes.

6. Discussion

The theoretical analysis presented in this study provides a nuanced understanding of how SIFT, SURF, and ORB respond to the degrading effects of a noisy environment a common and critical challenge in real-world image acquisition. The results reveal a clear performance hierarchy rooted in the mathematical foundations of each algorithm, which dictates their suitability for noise-prone panoramic stitching.

SIFT is known for being good at handling noise because it uses a scale-space method with Difference-of-Gaussians (DoG). This method reduces high-frequency noise before detecting keypoints by applying Gaussian smoothing. It also uses a 128-dimensional gradient histogram to combine local orientation data, which helps to minimize pixel noise. However, this process requires a lot of computing power and memory, making SIFT less suitable for limited-resource or real-time applications. ORB, while offering exceptional speed, suffers from a fundamental structural vulnerability to AWGN. Its FAST detector relies on comparing raw pixel intensities along a circle, a process highly sensitive to random intensity perturbations. Similarly, the BRIEF descriptor encodes binary tests based on pairwise pixel comparisons, which AWGN can easily invert, corrupting the descriptor's uniqueness. Consequently, even moderate noise levels lead to a sharp drop in correct matches, as corroborated by empirical studies. Thus, ORB's speed advantage is often negated in noisy environments unless a pre-processing denoising step is introduced, which adds latency and may inadvertently blur genuine features. SURF emerges as the most pragmatic compromise. By replacing the costly Gaussian convolutions with box filters computed via integral images, SURF drastically reduces computation time. It still captures directional energy in a manner less prone to single-pixel noise spikes. Empirical studies consistently report SURF retaining a higher percentage of valid matches than ORB under increasing Gaussian noise, while operating significantly faster than SIFT. This makes SURF particularly suitable for applications where moderate noise is expected such as in drone navigation or mobile augmented reality.

The role of the matching pipeline proves that FLANN accelerates correspondence estimation, its approximate nature may miss true matches in noisy, sparse descriptor spaces. Conversely, RANSAC acts as a powerful safeguard by iteratively fitting homographies and discarding outliers, it compensates for the initial mismatches caused by noise. However, if

the noise is severe enough to reduce the number of true inliers below the RANSAC threshold that corrupt the entire stitching process. In conclusion, no single algorithm offers a universal solution. The optimal choice depends on the operational context, requiring a careful trade-off. The core contribution of this review is:

- SIFT outcomes is highest accuracy in noise environment.
- SURF is the best trade-off for real-time performance with moderate noise.
- ORB is the highest speed and denoised environments

7. Conclusion and Future Work

This study established a rigorous theoretical foundation for evaluating the robustness of SIFT, SURF, and ORB against Additive White Gaussian Noise (AWGN) within the context of panoramic image stitching.

Our analysis conclusively demonstrates a clear performance hierarchy based on the underlying mathematical principles: 1. SIFT offers excellent noise resilience through multi-scale Gaussian smoothing and gradient-based descriptors that reduce high-frequency noise, but its high computational requirements render it impractical for real-time application. SURF provides the optimal trade-off between robustness and efficiency. By utilizing integral images, it achieves near-SIFT accuracy at a fraction of the computational cost, positioning it as the preferred choice for dynamic, noisy real-world applications. 3. ORB despite its superior speed, is highly vulnerable to AWGN due to its reliance on raw pixel intensities in both the FAST detector and the BRIEF descriptor, leading to substantial matching degradation even under moderate noise levels. The research stresses the post-processing pipeline's importance, focusing on FLANN and RANSAC. Selecting the best algorithm depends on noise level, computational limits, and the accuracy needs. We propose the following directions for future work:

- Noise-Hardened Binary Descriptors: Developing binary descriptors that retain ORB's computational speed while significantly improving AWGN resilience and speed.
- Deep Learning Denoising Integration: Empirically evaluating the integration of deep learning denoisers (e.g., FFDNet) as a pre-processing step to uniformly enhance the performance of all feature extractors under high noise.

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