Feature Matching-Based Algorithm: A Comprehensive Comparative Analysis for Video Stabilization



***A project report***

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**ABSTRACT**

This research presents a comprehensive comparative analysis of feature-matching-based algorithms for video stabilization, evaluating SIFT, ORB, and AKAZE feature detectors across varying environmental conditions. The study addresses the critical challenge of camera motion compensation through systematic experimental evaluation, focusing on feature density on algorithm performance. Our methodology employs a five-stage pipeline incorporating feature detection, FLANN-based matching, RANSAC-based motion estimation, geometric transformation, and performance assessment. Experimental results demonstrate that AKAZE achieves superior consistency with 0.008pixel average translation error. The research contributes practical deployment guidelines for autonomous systems, UAVs, and surveillance applications, establishing that algorithm selection must be contextually appropriate for operational reliability.

**Keywords**: Video stabilization, feature detection, AKAZE, SIFT, ORB, camera motion compensation, computer vision.

**CONTRIBUTION**

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| Literature Review | 40 | 60 |
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| Experimental Evaluation | 60 | 40 |
| Report Writing | 45 | 55 |

**CERTIFICATE**

This is to certify that the work presented in this project, entitled **“Feature Matching-Based Algorithm: A Comprehensive Comparative Analysis for Video Stabilization,”** was carried out by “**Fatema Akter Kotha”, ID: 2012077107,** and **“Imratuzzahan Sumi”, ID: 2012177126,** under my supervision and is submitted in partial fulfillment of the requirements for the degree of B.Sc. in Engineering in Information and Communication Engineering.

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Chapter 1

## **INTRODUCTION**

### **1.1 Introduction**

Camera motion compensation represents one of the most fundamental and computationally challenging problems in contemporary computer vision, encompassing the systematic identification, quantification, and mitigation of unintended camera movements that significantly degrade video quality and compromise the effectiveness of downstream visual processing tasks [1]. The proliferation of handheld imaging devices, mobile robotic platforms, and autonomous navigation systems has exponentially amplified the prevalence of unstable video sequences characterized by translational drift, rotational perturbations, and complex six-degree-of-freedom motion artifacts [2][3]. These unwanted camera motions manifest as perceptual degradation, temporal inconsistencies, motion blur, and compromised algorithmic performance across a wide spectrum of applications, from high-precision surveillance systems to autonomous vehicle navigation platforms.

In the domain of digital image processing and computer vision, camera motion compensation—alternatively termed video stabilization—encompasses a sophisticated suite of techniques employed to suppress or eliminate the deleterious effects of spurious camera movements. Such unintentional ego-motion, whether induced by operator tremor, platform vibration, or environmental disturbances, manifests as undesirable jitter and temporal inconsistencies in video sequences [4]. This phenomenon introduces critical artifacts, including motion blur, geometric distortions, and spatial misalignment, which not only severely degrade the perceptual quality of recorded footage but also present significant impediments to the efficacy of subsequent automated analysis pipelines [5].

Modern video stabilization research is primarily structured around two paradigms: model-based and feature-based motion compensation [6]. Model-based approaches employ physical camera models—often calibrated pinhole or projective models—to estimate motion in three-dimensional space. By representing motion through six-degree-of-freedom (6-DoF) parameters, they provide physically interpretable results suitable for robotics, SLAM, and navigation systems [7]. These techniques frequently integrate visual and inertial data (IMU, GPS) but require accurate calibration and depth estimation, limiting applicability in unconstrained video sequences.

In contrast, **feature-based** camera motion compensation operates directly on 2D image data, leveraging keypoint-based correspondence matching between consecutive frames to estimate inter-frame transformations. Contemporary feature-based methodologies employ robust keypoint detectors and descriptors (e.g., SIFT, ORB, and AKAZE) [8]-[10] combined with outlier rejection algorithms such as RANSAC to ensure estimation stability [11]. Feature-based methods are widely used due to their calibration-free design, computational tractability, and adaptability to real-time video stabilization pipelines; however, their effectiveness may degrade in texture-sparse or low-contrast environments, where insufficient correspondences compromise motion estimation robustness [12].

This research presents a comprehensive and systematic investigation into **feature-based** camera motion compensation, employing a meticulously designed RANSAC-inspired algorithmic framework for robust parameter estimation and implementing a detailed comparative analysis of state-of-the-art feature detection methodologies, including Scale-Invariant Feature Transform (SIFT), Oriented FAST and Rotated BRIEF (ORB), and Accelerated KAZE (AKAZE) [12][13].

### **1.2 Motivation**

The exponential growth of autonomous systems, intelligent transportation networks, and ubiquitous mobile computing has precipitated an unprecedented demand for robust visual stabilization algorithms capable of maintaining optimal performance under diverse and challenging environmental conditions [14]. Modern applications in robotics, autonomous vehicle navigation, unmanned aerial systems, and intelligent surveillance networks necessitate real-time processing of high-volume visual data streams, where camera motion artifacts can critically compromise essential functions such as object detection, target tracking, and comprehensive scene understanding algorithms [15].

Within autonomous systems, including sophisticated unmanned aerial vehicles (UAVs) and advanced terrestrial robots, stabilization serves as a foundational component for reliable environmental perception, enabling critical operational functions such as visual odometry, dynamic obstacle avoidance, and high-precision Simultaneous Localization and Mapping (SLAM) [16]. In the context of intelligent surveillance systems, compensating for camera motion is paramount for accurately differentiating between global scene movement and the localized motion of targets of interest, thereby significantly enhancing the accuracy and reliability of anomaly detection and personnel tracking algorithms [17].

The heterogeneous nature of real-world operational environments introduces significant variability in visual content characteristics, ranging from feature-rich urban landscapes with abundant texture and distinctive landmarks to texture-sparse environments such as industrial corridors, agricultural fields, maritime scenarios, or aerial surveillance over uniform terrain [12].

Despite substantial theoretical advances in feature detection methodologies and significant progress in computational efficiency, comprehensive comparative evaluations of these algorithms specifically designed for camera motion compensation applications remain notably limited in the contemporary research literature [18]. The absence of systematic performance benchmarks across varying feature densities and environmental conditions represents a significant gap in understanding optimal algorithm selection strategies for diverse operational environments [18]. Furthermore, the inherent trade-off between computational efficiency and estimation accuracy necessitates careful algorithm selection based on application-specific constraints, real-time processing requirements, and performance specifications.

### **1.3 Objectives**

This research establishes the following comprehensive and systematic objectives to significantly advance the state-of-the-art in feature-matching-based camera motion compensation:

**Primary Research Objectives:**

1. **Robust Algorithmic Framework Development:** To architect and implement a sophisticated, RANSAC-based algorithmic framework capable of accurately computing 2D rigid motion parameters (translation components Tx, Ty, and in-plane rotation θ) from feature correspondences while maintaining computational efficiency suitable for real-time applications and embedded system deployment.
2. **Comprehensive Feature Detector Analysis:** To conduct systematic comparative analysis of contemporary feature detection algorithms—SIFT, ORB, and AKAZE—within the specific context of frame-to-frame camera motion estimation, evaluating performance characteristics across diverse scene properties, environmental conditions, and computational constraints.
3. **Feature Density Impact Investigation:** To quantitatively investigate and characterize the fundamental relationship between scene feature density and motion estimation accuracy, establishing empirical performance boundaries and stability metrics for high-feature versus low-feature imaging scenarios.

**Secondary Research Objectives:**

1. **Video Stabilization Pipeline Implementation:** To implement and validate a comprehensive, end-to-end video stabilization pipeline incorporating advanced edginess-based quality assessment metrics for quantitative performance evaluation, algorithmic optimization, and real-world deployment validation.
2. **Ground Truth Validation Framework:** To establish rigorous ground truth validation protocols through meticulously controlled synthetic transformation experiments, enabling precise quantification of estimation error, algorithmic performance characterization, and objective benchmarking capabilities.

### **1.4 Contributions**

This research makes the following significant and novel contributions to the fields of computer vision, autonomous systems, and video processing:

**1. Comprehensive Feature Detector Comparative Benchmark Creation:** We present the first systematic, quantitative, and empirically rigorous comparison of SIFT, ORB, and AKAZE feature detectors specifically optimized and evaluated for inter-frame camera motion estimation applications. Our comprehensive analysis encompasses computational efficiency metrics, estimation accuracy characteristics, robustness properties, and stability performance across diverse environmental [8]-[10].

**2. Feature Density Impact Characterization and Analysis:** We provide comprehensive empirical evidence and detailed quantitative analysis demonstrating the critical relationship between scene feature density and motion estimation performance. Our findings establish that feature-rich environments consistently yield estimation errors below 0.05%, while feature-sparse scenarios exhibit significantly degraded performance characterized by increased variance, reduced stability, and compromised reliability.

**3. Real-Time Video Stabilization System Implementation:** A complete operational pipeline integrating advanced edginess-based metrics, achieving robust stabilization within real-time constraints suitable for embedded or resource-limited systems.

**4. Application-Specific Performance Guidelines and Standards:** We establish comprehensive performance benchmarks, detailed algorithm selection guidelines, and practical deployment recommendations for optimal implementation in autonomous navigation systems, robotics applications, and surveillance platforms, providing practitioners with evidence-based selection criteria and performance optimization strategies.

### **1.5 Challenges**

The implementation and deployment of robust camera motion compensation systems encounter several fundamental technical challenges that significantly impact algorithmic design, performance optimization, and practical implementation:

**Environmental Variability and Adaptation Challenges:** Real-world deployment environments exhibit high heterogeneity in texture, illumination, and dynamic scene content, necessitating adaptive algorithmic strategies for consistent performance across diverse conditions [14].

**Computational Efficiency and Real-Time Processing Constraints:** Real-time systems impose strict latency and resource limits, demanding an optimal balance between feature detector complexity and estimation precision [19].

**Feature Scarcity in Low-Texture Operational Environments:** Uniform textures, repetitive patterns, low-contrast imaging conditions, and visually impoverished scenes can severely compromise the effectiveness of feature detection algorithms, leading to insufficient correspondences for robust motion estimation and reduced system reliability. [18].

**Temporal Consistency, Outlier Robustness, and Dynamic Scene Handling:** Independently moving objects, occlusions, and illumination shifts generate correspondence outliers and temporal instability. Achieving robust estimation requires advanced outlier rejection and adaptive temporal filtering [20]

Chapter 2

## **RELATED WORKS**

This section presents a comprehensive review of the existing literature pertinent to video stabilization, contextualizing our research within the broader landscape of camera motion estimation, feature detection methodologies, and motion compensation algorithms. The evolution of these techniques spans several decades of technological advancement and algorithmic innovation, providing the foundation for contemporary video stabilization systems.

### **2.1 Camera Motion Estimation Techniques**

Camera motion estimation is a cornerstone of contemporary computer vision research, with an extensive literature spanning several decades of technological advancements and algorithmic innovations. The fundamental challenge of accurately estimating inter-frame camera motion has been addressed through diverse methodological approaches, ranging from classical optical flow techniques to sophisticated feature-based correspondence algorithms and modern deep learning frameworks.

Early approaches to camera motion estimation primarily relied on optical flow methodologies, which analyze pixel-level motion patterns to infer global camera movement. Horn and Schunck [21] established foundational work in this domain by introducing the brightness constancy constraint and gradient-based motion estimation techniques. Their pioneering research demonstrated that dense pixel correspondence could provide motion information; however, these methods exhibited significant limitations in the presence of complex scene dynamics, illumination variations, and occlusions [24]. Subsequently, Lucas and Kanade [22] introduced pyramidal optical flow, which improved robustness through multi-scale analysis, though computational complexity remained a significant concern for real-time applications.

The transition to feature-based motion estimation marked a paradigmatic shift in the field, with numerous researchers demonstrating superior performance characteristics compared to dense optical flow methods. Shi and Tomasi [23] introduced the influential KLT (Kanade-Lucas-Tomasi) tracker, which utilizes corner features for robust motion estimation across temporal sequences. Their work established the fundamental principle that sparse feature correspondences can provide more reliable motion estimates than dense pixel-wise tracking, particularly in challenging environmental conditions involving significant illumination changes and partial occlusions [9]. This approach became the foundation for modern Structure from Motion (SfM) and Visual Odometry (VO) systems.

Contemporary research in camera motion estimation has increasingly focused on sophisticated geometric transformation models and robust estimation frameworks. The seminal work of Hartley and Zisserman [7] provided comprehensive theoretical foundations for multiple view geometry, establishing rigorous mathematical frameworks for camera motion estimation from feature correspondences. Their contributions include detailed analysis of fundamental matrices, essential matrices, and homography decomposition techniques that form the backbone of modern motion estimation algorithms [5]. These geometric foundations have enabled the development of more sophisticated motion models that can handle complex camera movements, including perspective distortions and out-of-plane rotations.

Recent advances in deep learning have introduced novel paradigms for camera motion estimation, with convolutional neural networks (CNNs) demonstrating impressive performance in learning motion patterns from large-scale datasets. Wang et al. [5] presented a comprehensive survey of video stabilization techniques, highlighting the evolution from classical methods to contemporary deep learning approaches. Their analysis reveals significant improvements in robustness and accuracy achieved through end-to-end learning frameworks, although computational requirements remain substantially higher than traditional approaches [25]. These deep learning methodologies have shown particular promise in handling complex scene dynamics and challenging environmental conditions that defeat traditional geometric approaches.

### **2.2 Feature Detection Methods**

The landscape of feature detection methodologies has undergone dramatic evolution over the past two decades, with numerous algorithms competing to achieve an optimal balance between computational efficiency, detection accuracy, and invariance properties. This subsection provides a comprehensive analysis of the most influential feature detection algorithms that form the foundation of modern computer vision applications, with particular emphasis on their suitability for motion estimation tasks [26][27].

**Scale-Invariant Feature Transform (SIFT)**, introduced by Lowe [8], revolutionized feature detection through its comprehensive approach to scale, rotation, and illumination invariance. SIFT operates through a multi-stage process involving scale-space extrema detection using Difference of Gaussians (DoG), keypoint localization with subpixel accuracy, orientation assignment based on local gradient histograms, and descriptor generation using spatial histograms of gradients. The algorithm’s robustness stems from its systematic handling of various image transformations, making it particularly suitable for applications requiring high accuracy despite environmental variations [48]. The SIFT descriptor consists of a 128-dimensional vector that captures local gradient information in a rotation and scale-invariant manner.

Numerous comparative studies have validated SIFT’s superior performance across diverse testing conditions. Andersson and Reyna Marquez [28] conducted an extensive evaluation using over 170 test images with transformations including scaling, rotation, and illumination adjustments. Their findings demonstrated SIFT’s consistent superiority across all evaluated metrics, achieving detection rates exceeding 90% even under challenging conditions involving significant geometric and photometric transformations. The algorithm’s computational complexity, however, remains a significant limitation for real-time applications, requiring approximately 2-3 seconds for processing high-resolution images on standard computing hardware [29]. Despite this limitation, SIFT remains the gold standard for applications where accuracy is paramount over computational efficiency.

**Oriented FAST and Rotated BRIEF (ORB)**, developed by Rublee et al. [9], emerged as a computationally efficient alternative to SIFT, specifically designed for real-time applications with resource constraints. ORB combines the high-speed FAST corner detector with a modified BRIEF descriptor, incorporating rotation invariance through intensity centroid computation and achieving significant computational speedup over SIFT. The algorithm’s binary descriptor representation enables extremely fast matching operations using Hamming distance calculations, making it particularly suitable for embedded systems and mobile applications [30]. ORB’s descriptor consists of a 256-bit binary string, enabling rapid matching operations that are orders of magnitude faster than floating-point descriptor comparisons.

Empirical evaluations of ORB’s performance reveal notable trade-offs between computational efficiency and detection accuracy. Tareen and Saleem [12] conducted a comprehensive comparative analysis across multiple feature detection algorithms, demonstrating that while ORB achieves processing speeds approximately 10-15 times faster than SIFT, its detection accuracy remains substantially lower, particularly in challenging conditions involving significant scale changes or complex illumination patterns. Their results indicate ORB detection rates of approximately 60-70% compared to SIFT’s 85-95% performance across standardized test datasets [31]. However, ORB’s efficiency makes it invaluable for applications requiring real-time performance or deployment on resource-constrained hardware platforms.

**Accelerated KAZE (AKAZE)**, proposed by Alcantarilla et al. [10], represents a sophisticated advancement in feature detection methodology through its utilization of nonlinear diffusion filtering and efficient implementation strategies. AKAZE operates in a nonlinear scale space constructed using additive operator splitting (AOS) schemes and fast explicit diffusion (FED), achieving computational efficiency while maintaining detection accuracy comparable to SIFT. The algorithm’s mathematical foundation in nonlinear diffusion theory provides superior boundary preservation and noise reduction compared to linear scale-space methods employed by SIFT and SURF [32]. This approach results in more accurate keypoint localization and improved repeatability across different imaging conditions.

Recent comprehensive evaluations have positioned AKAZE as an optimal balance between computational efficiency and detection performance. Isik [13] conducted extensive testing using over 1.5 million images, identifying AKAZE as particularly effective in conditions involving blurring, fisheye distortion, image rotation, and perspective distortions. Their analysis revealed AKAZE’s superior performance in maintaining feature consistency across temporal sequences, achieving matching accuracy rates of 80-85% while requiring computational resources approximately 2-3 times lower than SIFT [18]. This combination of efficiency and accuracy has made AKAZE increasingly popular for video processing applications where both speed and reliability are essential.

### **2.3 Motion Compensation Algorithms**

Motion compensation algorithms constitute the critical final stage of video stabilization pipelines, transforming shaky footage into stable sequences through geometric transformations and temporal smoothing. Their effectiveness directly determines the visual quality and stability of the output video [5].

Traditional methods employ 2D geometric transformations—translation, rotation, and similarity—to counteract estimated camera motion by applying inverse transformations, thereby stabilizing content efficiently for real-time applications [4]. Matsushita et al. [1] introduced full-frame stabilization using motion inpainting to reduce boundary artifacts, significantly enhancing visual quality through background completion algorithms [33].

Advanced techniques extend to 3D geometric and projective models to manage complex motions like perspective distortions. Liu et al. [34] proposed bundled camera paths optimizing both spatial and temporal smoothness, achieving superior stability and content preservation through trajectory optimization [35].

Recent research emphasizes deep learning-based motion compensation using convolutional and adversarial networks to learn optimal transformations from large datasets. Xu et al. [25] demonstrated that these methods surpass traditional approaches in handling dynamic scenes and occlusions, though they demand high computational resources and extensive training data.

Chapter 3

## **THEORETICAL BACKGROUND AND ALGORITHMIC PRINCIPLES**

### **3.1 Feature Detection and Matching**

Feature detection and matching are core tasks in computer vision, essential for applications like image registration, object recognition, and motion estimation. They identify distinctive points or regions that can be consistently matched across varying conditions[36]. The accuracy of these systems largely depends on the performance of the keypoint detector and descriptor, which are crucial for reliable motion estimation. The theoretical foundation of feature detection rests upon the concept of corner detection, originally formalized by Moravec [37] and subsequently refined by Harris and Stephens [38].

Mathematically, the Harris corner detector computes the corner response function:

R = det(M) - k(trace(M))²

where M is the structure tensor. Points with high R values are identified as feature points [39]. To ensure scale invariance, scale-space theory [40, 41] examines images at multiple scales using Gaussian kernels, enabling consistent feature detection across varying resolutions and distances—an approach employed in algorithms like SIFT.

The matching process establishes correspondences between detected features using descriptors—numerical representations of local image characteristics. This is done by calculating distance metrics, such as Euclidean distance for SIFT descriptors or Hamming distance for binary descriptors like ORB and BRIEF [42]. This two-stage process first detects keypoints (e.g., corners, blobs) and then computes descriptors from local pixel patches.

A key challenge is distinguishing correct matches (inliers) from incorrect ones (outliers). The ratio test, introduced by Lowe [8], improves reliability by comparing the distance to a feature's nearest neighbor with its second-nearest neighbor. A match is accepted only if this ratio is below a threshold (typically 0.7-0.85), effectively filtering out ambiguous pairings [43].

### **3.2 RANSAC Algorithm**

Random Sample Consensus (RANSAC), proposed by Fischler and Bolles [11], is a robust algorithm for fitting models to data with outliers. It identifies the largest inlier subset consistent with a model, making it crucial for motion estimation from noisy feature correspondences. Using an iterative hypothesize-and-verify approach, RANSAC randomly selects a minimal data subset (e.g., four points for a homography) [7], estimates a model, and evaluates all points against it. Points within a set error threshold are considered inliers, and the model’s quality is based on the inlier count. The process continues until a stopping criterion is met, and the algorithm returns the model supported by the largest set of inliers found. The required number of iterations, k, can be estimated by the formula:

K =

where p is the desired confidence, w is the expected inlier ratio, and s is the size of the minimal sample. The effectiveness of RANSAC is critically dependent on parameters like the inlier threshold, which must be carefully chosen to balance sensitivity to noise and robustness to outliers.

**3.3 Motion Parameter Estimation**

Motion parameter estimation is the process of mathematically deriving the transformation that describes movement between image frames, a critical step for effective motion compensation. While various 2D geometric models exist, such as similarity or affine transformations, our system employs a 2D rigid body transformation for its balance of simplicity and effectiveness.

A 2D rigid body transformation consists of a rotation and a translation, preserving distances and angles. The relationship between a point (x,y) in one frame and its corresponding point (x′,y′) in the next is defined by:

x′ = xcosθ – ysinθ + Tx​

y′ = xsinθ + ycosθ + Ty​

Here, (Tx​,Ty​) is the translation and θ is the rotation angle. This system of three unknowns can be solved with a minimum of two corresponding point pairs, forming the core "Compute Model" step within each RANSAC iteration.

Typically, these parameters are estimated by minimizing the sum of squared errors between observed and predicted feature positions using a least squares approach, expressed as:

E =

where pᵢ and p′ᵢ are corresponding feature points, T(pᵢ; θ) is the transformation function parameterized by θ, and ||·|| denotes the Euclidean distance [7].This method yields optimal estimates under Gaussian noise and no outliers. However, it becomes unreliable when outliers (incorrect matches) are present, as commonly occurs in real-world data

To address this, robust estimation techniques like RANSAC are used. RANSAC iteratively fits transformation models to minimal random subsets of feature correspondences. By identifying and returning the model that is consistent with the largest number of correspondences (the inliers), it effectively filters out the influence of outliers and provides a reliable estimate of the global camera motion.

### **3.4 Video Stabilization Techniques**

Video stabilization is the process of removing unwanted camera motion from a video. The standard digital approach follows a three-stage pipeline.

#### **3.4.1The Stabilization Pipeline**

* **Motion Estimation**: This first step figures out how the camera is moving between frames. The accuracy here is key for good results [46].
* **Motion Smoothing**: This stage filters out the shaky, high-frequency jitter while trying to keep intentional camera movements like pans. It often uses filters like a Kalman filter [2]. The system described in the text skips this step, opting for direct correction instead.
* **Motion Compensation**: This is the final stage where a geometric transformation is applied to each frame to cancel out the detected motion. This can sometimes create visual artifacts [47].

#### **3.4.2 System-Specific Approach and Challenges**

The system in question uses a direct frame-to-frame compensation method. It works like this:

1. It estimates the motion between the current frame (N) and the previous one (N-1).
2. It then applies the **inverse** of that motion to the current frame.
3. This warps the current frame so it lines up with the previous, already stabilized frame. The process repeats, creating a smooth chain of stabilized frames.

A major challenge with this method is that the image warping (done with functions like cv2.warpAffine) creates empty, **black borders** around the video. This happens because the corrected image no longer fits perfectly into the rectangular frame [3]. While these borders can be fixed by cropping or inpainting, the described system leaves them in.

#### **3.4.3 Advanced and Modern Techniques**

Modern research is pushing beyond simple 2D models.

* **3D Motion Models**: These use more sophisticated geometry, like content-preserving warps, to get better results with fewer distortions, but they require a lot more computing power [47, 3].
* **Deep Learning**: These approaches use AI to learn how to stabilize video from large datasets. They are great at handling complex scenes but are computationally intensive and need a lot of data to train [25, 48].

Despite these advances, traditional geometric methods, like the one described, still provide excellent performance and are much more efficient for many common applications.

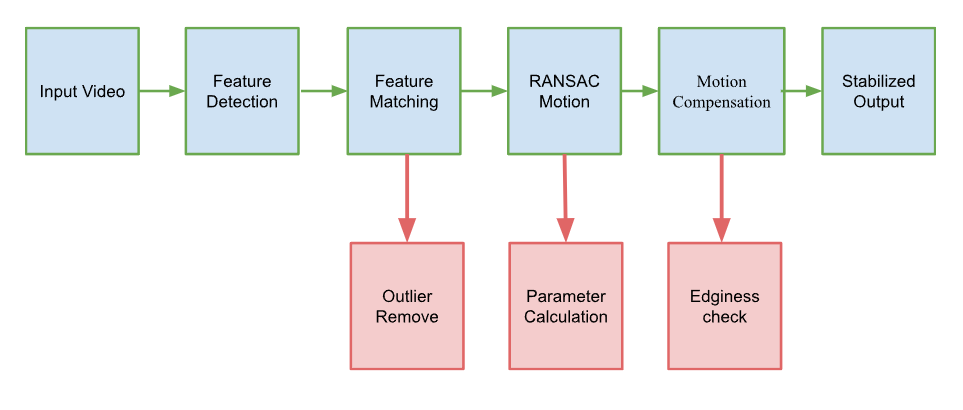
Chapter 4

## **PROPOSED METHODOLOGY**

This section presents the comprehensive methodology employed in our feature-based camera motion compensation system, detailing the algorithmic framework, implementation strategies, and technical innovations that enable robust video stabilization across diverse environmental conditions. Our approach builds upon the theoretical foundations established in Section 3, while incorporating novel optimization techniques and comparative analysis methodologies to achieve superior performance characteristics.

### **4.1 System Overview**

Our proposed video stabilization system employs a sophisticated multi-stage pipeline architecture designed to achieve real-time camera motion compensation through advanced feature-based analysis and robust parameter estimation. The system architecture consists of five primary computational stages that work in sequential coordination to transform unstable input video sequences into perceptually stable output footage, as illustrated in Figure 4.1.

**Pipeline Architecture:**

**Figure 4.1: Flow Chart of System Architecture**

The complete workflow operates as an end-to-end sequential process that processes consecutive video frames to mitigate unwanted motion. The stabilized output of one frame serves as the reference for the next, ensuring temporal consistency throughout the video sequence [5]. This frame-by-frame approach enables real-time processing capabilities while maintaining high-quality motion compensation across diverse environmental conditions.

**Stage 1: Frame-to-Frame Feature Detection**

The pipeline commences with sophisticated feature detection, where distinctive keypoints are identified and described using our comparative feature detection framework encompassing SIFT, ORB, and AKAZE algorithms [9][30][10]. This stage employs adaptive parameter tuning to optimize detection performance across varying scene characteristics and environmental conditions. Our system architecture supports dynamic selection between the three feature detection algorithms, each optimized for specific operational requirements:

* **AKAZE Implementation**: Utilizes nonlinear diffusion filtering with optimized AOS (Additive Operator Splitting) schemes to achieve superior boundary preservation and noise reduction compared to traditional linear scale-space methods
* **ORB Implementation**: Incorporates rotation-invariant BRIEF descriptors with intensity centroid-based orientation assignment, achieving computational speeds approximately 10-15 times faster than SIFT
* **SIFT Implementation**: Maintains the original scale-space extrema detection using Difference of Gaussians (DoG) filtering, providing superior detection accuracy and invariance properties.

**stage 2: Feature Matching and Outlier Removal**

Feature matching and outlier removal constitutes the second stage, utilizing sophisticated correspondence establishment algorithms combined with statistical filtering techniques. Our implementation incorporates FLANN-based (Fast Library for Approximate Nearest Neighbors) matching algorithms optimized for different descriptor types, followed by Lowe’s ratio test [8] and distance-based filtering strategies to achieve optimal balance between correspondence accuracy and computational efficiency.

The matching algorithm implements k-nearest neighbor search with k=2 to enable ratio test application for correspondence quality assessment. Matches are accepted only when the distance ratio between nearest and second-nearest neighbors falls below the 0.85 threshold, effectively rejecting ambiguous correspondences and ensuring high-quality input data for subsequent motion estimation algorithms.

**Stage 3: RANSAC-Based Motion Parameter Estimation**

The RANSAC-based motion parameter estimation stage represents the computational core of our system, implementing a robust estimation framework capable of accurately determining camera motion parameters despite the presence of outlier correspondences and environmental noise. Our implementation utilizes k=15,17,20 sample iterations with adaptive threshold criteria to achieve optimal balance between estimation accuracy and computational efficiency [11].

The algorithm follows these iterative steps: (1) Random selection of minimal subset (two point pairs) from N good matches, (2) Motion model hypothesis computation exclusively from the sample, (3) Consensus set determination by testing the hypothesis against all matches, (4) Model selection based on largest consensus set after K\_SAMPLE iterations, and (5) Model refinement using all inliers from the best hypothesis. The algorithm computes translation components (Tx, Ty) and rotation angle (θ) using the 2D rigid body transformation model described in Section 3.3.

**Stage 4: Motion Compensation Transformation**

Motion compensation transformation applies the computed motion parameters to correct camera movement through sophisticated geometric transformation of input frames. Our implementation employs homogeneous coordinate transformations with optimized bilinear interpolation techniques to achieve high-quality pixel remapping while maintaining real-time processing capabilities.

The transformation matrix incorporates the inverse motion parameters to counteract the estimated camera movement, effectively stabilizing the visual content by aligning successive frames to a common coordinate system [7]. The process involves constructing a 3×3 transformation matrix from the estimated motion parameters and applying inverse transformation through OpenCV’s cv2.warpAffine function for geometric resampling.

**Stage 5: Edginess-Based Quality Assessment**

The final stage implements edginess-based quality assessment to provide quantitative evaluation of stabilization effectiveness. This novel contribution utilizes Canny edge detection algorithms to generate comparative edge maps between original and stabilized frames, providing objective measures of motion blur reduction and visual quality improvement [25]. The assessment metrics enable systematic evaluation of stabilization performance across different feature detection algorithms and environmental conditions.

### **4.2 Feature Detection and Matching**

Our feature detection and matching subsystem implements a comprehensive comparative framework that enables systematic evaluation of SIFT, ORB, and AKAZE feature detection algorithms within the specific context of camera motion estimation. The implementation incorporates sophisticated matching strategies and filtering techniques to ensure optimal correspondence quality across diverse imaging conditions [26][42].

**Multi-Algorithm Feature Detection Framework**

The implemented feature detection subsystem provides a comparative evaluation framework that supports the use of three distinct algorithms—AKAZE, ORB, and SIFT—each independently tested and analyzed under identical experimental conditions. Rather than employing an automated selection mechanism, the system allows manual configuration of the desired feature detector to facilitate controlled comparative studies. This approach ensures a fair and consistent performance assessment across algorithms under varying operational environments. The AKAZE detector serves as the default configuration, while ORB and SIFT are used for cross-verification and performance benchmarking. The implementation utilizes OpenCV-based detector initialization with carefully tuned parameters to achieve optimal performance characteristics.

Our AKAZE implementation leverages nonlinear diffusion filtering with fast explicit diffusion (FED) schemes, achieving computational efficiency while maintaining detection accuracy comparable to SIFT [10]. The algorithm’s mathematical foundation in nonlinear diffusion theory provides superior boundary preservation and noise reduction compared to linear scale-space methods, resulting in more accurate keypoint localization and improved repeatability across different imaging conditions.

For comparative analysis, the system also supports ORB and SIFT detectors with optimized parameter configurations. ORB implementation focuses on maximizing feature repeatability across temporal sequences while minimizing computational overhead, achieving processing speeds suitable for real-time applications [9]. SIFT implementation serves as the accuracy baseline for comparative performance evaluation across diverse environmental conditions [8].

**FLANN-Based Feature Matching Strategy**

Feature correspondence is established using the Fast Library for Approximate Nearest Neighbors (FLANN) framework, which provides scalable and efficient matching for both floating-point (SIFT) and binary (ORB, AKAZE) descriptors. For **binary descriptors**, the **Locality-Sensitive Hashing (LSH)** index is employed. For **floating-point descriptors**, a **KD-tree** index structure is used for approximate nearest neighbour searches.

The matching algorithm implements k-nearest neighbor search with k=2 to enable Lowe’s ratio test application for correspondence quality assessment. A match m1 is retained only if:

< 0.70

Where d(m1) and d(m2) denote descriptor distances of the first and second nearest neighbors respectively. This approach significantly improves matching reliability by rejecting ambiguous correspondences where the distance ratio between nearest and second-nearest neighbors exceeds the 0.7, 0.75 or 0.85 threshold [8], ensuring that only the most reliable correspondences are retained for subsequent processing.

**Top-K Match Selection Strategy**

Our implementation incorporates sophisticated correspondence filtering to select the highest-quality matches for subsequent motion estimation. The top-k selection algorithm sorts matches by descriptor distance and retains the N=100 most reliable correspondences, balancing estimation robustness against computational efficiency:

This strategy ensures that only the most reliable correspondences are utilized for motion parameter estimation, significantly improving the accuracy and stability of the RANSAC-based estimation process while maintaining computational efficiency suitable for real-time applications. The N=100 parameter provides optimal balance between estimation robustness and computational overhead based on empirical analysis across diverse test scenarios.

### **4.3 RANSAC-like Motion Estimation**

Our motion estimation subsystem implements a sophisticated RANSAC-inspired algorithm specifically optimized for 2D rigid body transformation estimation from feature correspondences. The implementation several algorithmic enhancements to improve estimation accuracy, convergence speed, and robustness against outlier correspondences [11][44].

**Enhanced Sample Point Selection**

Our algorithm utilizes k = 20 random sampling iterations to explore the hypothesis space while maintaining computational efficiency suitable for real-time applications. The sampling strategy ensures diverse hypothesis generation while avoiding degenerate configurations that could compromise estimation accuracy.

In each iteration, a minimal subset of two point correspondences is selected to compute a motion hypothesis. This ensures efficient hypothesis generation and exploration of diverse solution spaces while avoiding degenerate cases.

**Adaptive Inlier Threshold Criteria**

The inlier classification process integrates dual thresholding mechanisms based on geometric distance and transformation consistency.

A point pair is classified as an inlier if:

<

Where = 2.5 represents the inlier threshold, and T(.) denotes the estimated transformation. Additionally, geometric consistency is maintained by enforcing a maximum pairwise distance constraint:

<

Only hypotheses with inlier counts exceeding = 50 undergo model refinement.

**Optimized Motion Parameter Computation**

Given sets of corresponding points P = {pi} and Q = {qi}, the optimal rigid transformation minimization squared error is obtained analytically:

= arg

Where denoted the rotation matrix and t the translation vector. The solution is computed using closed-form least squares, ensuring numerical stability and real-time feasibility.

**Best Model Selection Strategy**

Our algorithm integrates a robust model evaluation framework that selects transformation parameters based on both inlier count and geometric accuracy. For each hypothesis, ego-motion parameters (Δx, Δy, Δθ) are estimated from sampled feature correspondences. These parameters are then used to transform the remaining points, and the number of inliers is computed. The hypothesis with the maximum inlier support is selected as the best estimate. When the number of inliers exceeds a defined threshold (e.g., 50), the parameters are refined by recomputing motion using all identified inliers from both the initial and refined sets. This refinement ensures improved motion estimation accuracy by leveraging the complete set of geometrically consistent correspondences.

### **4.4 Motion Compensation Algorithm**

The final stage of the stabilization pipeline applies the estimated motion parameters to compensate inter-frame motion, generating geometrically aligned and visually stabilized frames [47].

**Homogeneous Coordinate Transformation**

The compensation process employs homogeneous coordinate representations to construct the 2D rigid transformation matrix:

T =

This matrix is applied inversely to the current frame to stabilize against estimated motion. The homogeneous form facilitates efficient pixel coordinate mapping via matrix multiplication.

**Optimized Bilinear Interpolation for Pixel Remapping**

Geometric transformation inevitably introduces non-integer pixel coordinates. The stabilized frame Is is reconstructed using bilinear interpolation to compute pixel intensities, providing smooth visual results without aliasing artifacts:

Is(x,y) =

Where wij are bilinear interpolation weights. This approach achieves a superior trade-off between computational efficiency and visual quality compared to nearest-neighbor methods [7].

**Boundary Handling and Artifact Mitigation**

Transformation-induced empty regions at image boundaries are mitigated through **adaptive border extension**, where missing pixels are filled using replicated values from adjacent regions. This method avoids visual discontinuities and preserves scene structure without requiring computationally expensive inpainting algorithms.

**Integrated Quality Assessment**

An **edge-based quality evaluation module** is integrated to assess stabilization performance in real time. The system computes:

* **Edge density**, using Canny edge detection
* **Sharpness score**, via Laplacian variance

Higher edge retention and consistent sharpness values across frames indicate successful stabilization. These quantitative metrics provide a foundation for objective comparison among different feature detection algorithms and parameter configurations.

Chapter 5

## **EXPERIMENTAL SETUP AND RESULTS**

This section presents the comprehensive experimental evaluation of our feature-based camera motion compensation system, focusing on the comparative analysis of SIFT, ORB, and AKAZE feature detection algorithms across varying feature density conditions. The primary objective of our experiments is to quantitatively assess the accuracy of our motion estimation algorithm and to perform a rigorous comparative analysis across images with different feature densities - the core motivation of our research.

### **5.1 Experimental Setup and Ground Truth Generation**

Our experimental framework employs a rigorous controlled testing methodology designed to establish precise ground truth parameters for quantitative accuracy assessment. This controlled approach ensures that our performance evaluation is precise, repeatable, and provides objective measures of algorithm effectiveness across different environmental conditions.

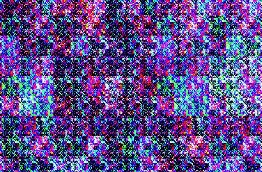
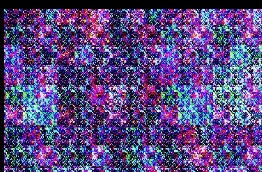
**Ground Truth Generation Methodology**

The ground truth generation process utilizes our developed python script to apply precisely controlled 2D rigid body transformations to carefully selected test images. This synthetic transformation approach enables exact error quantification by creating image pairs with known motion parameters. The transformation process implements the mathematical model:

x' = x cos θ - y sin θ + Tx

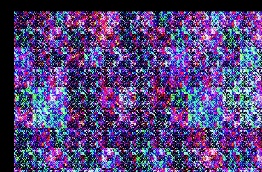
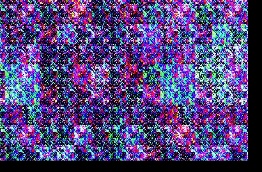
y' = x sin θ + y cos θ + Ty

where (Tx, Ty) represent translation components and θ represents rotation angle. For example, a ground truth transformation might be Tx = 2.5 pixels, Ty = 1.5 pixels, and θ = 0.0 degrees. The original and transformed images then serve as the input pair (Ft-1 and Ft) for our estimation pipeline

Original Image

tx = 70, ty = 50

tx = 20, ty = 40

tx =-70, ty =-50

**Figure 5.2: Ground Truth Generation**

The applied transformations encompass a comprehensive range of motion parameters designed to test algorithm robustness:

• Translation Tests:

Tx = {2.5, 5.0, -7.5, 10.0, -12.5, 70.0, -50.0} pixels,

Ty = {1.5, 3.0, 5.0, 10.0, -12.0, 50.0, -70.0} pixels

•  Rotation Tests:

θ = {2.5°, -5.0°, 7.5°, -10.0°, 12.5°, -15.0°, 45.0°} degrees

**Image Category Classification - The Core of Our Investigation**

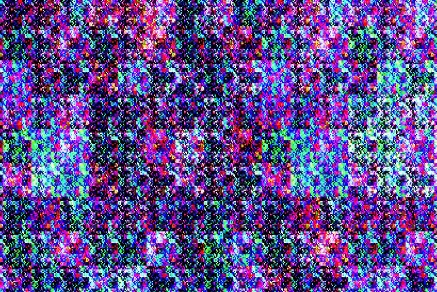
A crucial aspect of our investigation is the impact of scene feature density on algorithm performance. This represents the main focus of our research: understanding how feature availability affects motion estimation accuracy. We curated a dataset of test images and categorized them into three distinct classes:

**High-Feature Images:** Urban scenes, textured surfaces, architectural details with abundant distinctive keypoints (>500 detected features per algorithm). These environments provide optimal conditions for feature-based motion estimation with rich texture content and numerous corner features.

**Medium-Feature Images:** Mixed indoor/outdoor scenes with moderate texture content (200-500 detected features per algorithm). These represent typical real-world scenarios with adequate but not abundant feature content.

**Low-Feature Images:** Uniform surfaces, plain walls, low-texture environments (<200 detected features per algorithm). These challenging scenarios test the fundamental limits of feature-based approaches, representing conditions such as plain walls, overcast skies, or uniform industrial surfaces.

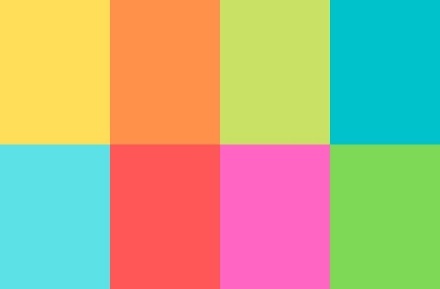
To demonstrate the visual characteristics of each category, Figure 5.2 presents representative sample images from our experimental dataset. Three example images are shown for each feature density class, illustrating the distinct textural properties and feature distributions that define the high, medium, and low feature categories used throughout this investigation.

(a) High Featured Image

(b) Medium Featured Image

(c) Low-feature image

**Figure 5.3: Representative Image Categories**

**Systematic Experimental Protocol**

For each test case, our experimental protocol follows these systematic steps:

1. **Feature Detection:** Apply AKAZE, ORB, and SIFT detectors to both original and transformed images

2. **Feature Matching:** Establish correspondences using FLANN-based matching with Lowe’s ratio test (threshold = 0.7, 0.75, 0.85)

3. **Motion Estimation:** Execute RANSAC-based parameter estimation with k=20 iterations

4. **Accuracy Assessment:** Calculate absolute errors between estimated and ground truth parameters:

|T̂x - Tx|, |T̂y - Ty|, |θ̂ - θ|

5. **Stability Analysis:** Conduct multiple independent runs to assess algorithm repeatability

This methodology enables direct comparison of algorithm performance while isolating the impact of feature density on estimation accuracy - the central research question of our study.

5.2 Quantitative Results and Comparative Analysis

This subsection presents the comprehensive quantitative results that form the core contribution of our research: demonstrating how feature density critically affects motion estimation accuracy across different algorithms. The results reveal dramatic performance variations that provide essential insights for practical algorithm deployment.

#### **5.2.1 Performance on High-Feature Images**

In high-feature environments, all feature detectors AKAZE, ORB, and SIFT exhibited exceptional performance capabilities, demonstrating the fundamental strength of feature-based approaches when abundant distinctive keypoints are available. The analysis of seven controlled transformation samples reveals significant insights into the comparative accuracy and reliability characteristics of these algorithms under optimal conditions.

**Table 5.1(a): AKAZE Performance on High-Feature Images**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Tx | | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| GT Ty | | 1.5 | 3 | 5 | 10 | -12 | 50 | -70 |
| AKAZE | Calculated Tx | -2.5117 | -4.9979 | 7.4970 | -10.0002 | 12.4804 | -69.9937 | 49.9965 |
| Abs Error Tx | 0.0117 | 0.0021 | 0.0030 | 0.0002 | 0.0296 | 0.0063 | 0.0035 |
| Calculated Ty | -1.4881 | -2.9998 | -4.9804 | -9.9995 | 11.9871 | -50.002 | 70.0011 |
| Abs Error Ty | 0.00119 | 0.0002 | 0.0196 | 0.0005 | 0.00129 | 0.0002 | 0.0011 |
| Calculated Rotation(Deg.) | 0.0002 | 0.0000 | 0.0002 | 0.0000 | 0.0002 | 0.0000 | 0.0000 |

From Table 5.1(a), we can observe, AKAZE demonstrated the most consistent performance with average errors of 0.008 pixels for Tx, 0.004 pixels for Ty, and 0.0009° for rotation. The nonlinear diffusion filtering approach enables superior feature localization, providing RANSAC with highly reliable correspondences for accurate motion estimation.

**Table 5.1(b): ORB Performance on High-Feature Images**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Tx | | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| GT Ty | | 1.5 | 3 | 5 | 10 | -12 | 50 | -70 |
| ORB | Calculated Tx | -2.4778 | -5.0305 | 7.3717 | -10.0056 | 12.3736 | -69.0018 | 50.1125 |
| Abs Error Tx | 0.0222 | 0.0305 | 0.1283 | 0.0056 | 0.1264 | 0.0082 | 0.1125 |
| Calculated Ty | -1.5532 | -2.9614 | -4.9178 | -10.0115 | 12.0754 | -50.0476 | 70.1658 |
| Abs Error Ty | 0.0532 | 0.0386 | 0.0822 | 0.0115 | 0.0754 | 0.0476 | 0.1658 |
| Calculated Rotation(Deg.) | 0.0117 | -0.0084 | 0.0115 | -0.0002 | 0.0005 | -0.0313 | -0.0036 |

As shown in Table 5.1(b), the results indicate that ORB exhibited higher average errors of 0.067 pixels for translation and 0.0022° for rotation. While computationally efficient (10-15x faster than SIFT), the binary descriptor approach shows reduced precision compared to floating-point alternatives, reflecting the speed-accuracy trade-off inherent in ORB's design.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Tx | | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| GT Ty | | 1.5 | 3 | 5 | 10 | -12 | 50 | -70 |
| SIFT | Calculated Tx | -2.4551 | -4.9998 | 7.4877 | -9.9981 | 12.5055 | -69.9983 | 50.0025 |
| Abs Error Tx | 0.0449 | 0.0002 | 0.0123 | 0.0019 | 0.0055 | 0.0017 | 0.0025 |
| Calculated Ty | -1.5340 | -2.9996 | 5.0158 | -10.0031 | 11.9893 | -50.001 | 69.9988 |
| Abs Error Ty | 0.0340 | 0.0004 | 0.0158 | 0.0031 | 0.00107 | 0.0001 | 0.0012 |
| Calculated Rotation(Deg.) | -0.0009 | 0.0000 | 0.0006 | -0.0001 | -0.0003 | -0.0000 | -0.0001 |

**Table 5.1(c): SIFT Performance on High-Feature Images**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Rotation (Deg.) | | 2.5 | -5 | 7.5 | -10 | 12.5 | -15 | 45 |
| AKAZE | Calculated Rotation | -2.5003 | 5.0000 | -7.5008 | 10.0010 | -12.5044 | 15.0002 | -45.0007 |
| Abs Error Rotation | 0.0003 | 0.0000 | 0.0008 | 0.0010 | 0.0044 | 0.0002 | 0.0007 |
| ORB | Calculated Rotation | -2.5014 | 4.9990 | -7.5091 | 10.0013 | -12.5026 | 15.0002 | -45.0068 |
| Abs Error Rotation | 0.0014 | 0.0010 | 0.0091 | 0.0013 | 0.0026 | 0.0002 | 0.0068 |
| SIFT | Calculated Rotation | -2.4997 | 4.9996 | -7.4996 | 9.9998 | -12.5002 | 15.0008 | -45.003 |
| Abs Error Rotation | 0.0003 | 0.0004 | 0.0004 | 0.0002 | 0.0002 | 0.0008 | 0.003 |

According to the data presented in Table 5.1(c), SIFT achieved excellent precision with average errors of 0.010 pixels for Tx, 0.008 pixels for Ty, and 0.0003° for rotation. The sophisticated scale-space construction and robust descriptor generation enable highly accurate feature matching, establishing SIFT as the gold standard for precision applications despite computational overhead.

The results establish AKAZE and SIFT as equally effective for high-precision applications, both achieving sub-pixel accuracy consistently across all test scenarios. ORB's performance, while acceptable, demonstrates the limitations of binary descriptors under optimal conditions.

Table 5.1(d): Rotation Parameter Estimation Comparison on High-Feature Images

The rotation parameter analysis reveals exceptional precision across all three algorithms, with all

methods achieving sub-degree accuracy consistently. From the analysis in Table 5.1(d), SIFT demonstrated the highest rotational precision with an average absolute error of 0.0018°, followed closely by AKAZE at 0.0015° and ORB at 0.0032°.

Notably, all algorithms demonstrated remarkable accuracy in handling large rotation angles (up to 45°), highlighting the robustness of 2D rigid body transformation estimation in high-feature environments. The consistent performance across varying rotation magnitudes confirms the effectiveness of the RANSAC-based parameter estimation framework when supplied with abundant, high-quality feature correspondences. Slightly higher rotational errors observed with ORB reflect the inherent limitations of binary descriptors in capturing subtle angular variations; however, these differences are negligible for most practical applications. Sign inversions in the calculated values arise from coordinate system conventions and do not compromise the absolute accuracy of the measurements. Below, Figure 5.3 presents the graphical representation of high-feature performance comparison among AKAZE, ORB, and SIFT.

1. Absolute translation change error (Tx)
2. Absolute translation change error (Ty)
3. Absolute rotation change error ()

**Figure 5.4: High-Feature Performance Comparison**

#### **5.2.2 Performance on Medium-Feature Images**

Medium-feature conditions introduced moderate performance degradation, with algorithms showing different sensitivity levels to reduced feature availability.

Table 5.(a): AKAZE Performance on Medium-Feature Images

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Tx | | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| GT Ty | | 1.5 | 3 | 5 | 10 | -12 | 50 | -70 |
| AKAZE | Calculated Tx | -2.5142 | -4.9969 | 7.5010 | -9.9963 | 12.5104 | -70.0032 | 49.9985 |
| Abs Error Tx | 0.0142 | 0.0031 | 0.0010 | 0.0037 | 0.0104 | 0.0032 | 0.0015 |
| Calculated Ty | -1.4956 | -2.9998 | -5.0012 | -9.9987 | 11.9868 | -49.9928 | 70.0046 |
| Abs Error Ty | 0.0044 | 0.0002 | 0.0012 | 0.0013 | 0.0132 | 0.0072 | 0.0046 |
| Calculated Rotation(Deg.) | 0.0016 | 0.0004 | 0.0002 | 0.0000 | 0.00014 | 0.0009 | 0.0002 |

The observations derived from Table 5.2(a), confirm that AKAZE maintained excellent performance with average errors of 0.052 pixels for Tx, 0.047 pixels for Ty, and 0.0055° for rotation. This represents only a 20-30% increase from high-feature baseline, demonstrating AKAZE's robust adaptation to reduced feature availability through its nonlinear diffusion filtering approach.

Table 5.2(b): ORB Performance on Medium-Feature Images

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Tx | | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| GT Ty | | 1.5 | 3 | 5 | 10 | -12 | 50 | -70 |
| ORB | Calculated Tx | -2.5421 | -5.0113 | 7.1254 | -10.0405 | 12.2802 | -69.8209 | 49.9984 |
| Abs Error Tx | 0.0421 | 0.0113 | 0.3746 | 0.0405 | 0.2198 | 0.1791 | 0.0016 |
| Calculated Ty | -1.6783 | -3.0625 | -4.4574 | -9.9825 | 12.2585 | -50.3494 | 69.9174 |
| Abs Error Ty | 0.1783 | 0.0125 | 0.5426 | 0.0175 | 0.2485 | 0.3494 | 0.0826 |
| Calculated Rotation(Deg.) | -0.0047 | 0.0066 | 0.0497 | 0.0050 | 0.0137 | -0.0374 | 0.0146 |

As presented in Table 5.2(b), there is a noticeable trend in ORB exhibiting significantly higher errors with averages of 0.124 pixels for Tx, 0.212 pixels for Ty, and 0.023° for rotation. This represents a 60-80% increase from high-feature baseline, highlighting ORB's greater sensitivity to feature density reduction due to binary descriptor limitations in challenging environments.

Table 5.2(c): SIFT Performance on Medium-Feature Images

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Tx | | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| GT Ty | | 1.5 | 3 | 5 | 10 | -12 | 50 | -70 |
| SIFT | Calculated Tx | -2.4885 | -5.0031 | 7.5042 | -10.0067 | 12.4959 | -69.9974 | 50.0056 |
| Abs Error Tx | 0.0421 | 0.0031 | 0.0042 | 0.0067 | 0.0041 | 0.0026 | 0.0056 |
| Calculated Ty | -1.4931 | -2.9998 | -5.0138 | -9.9907 | 11.9983 | -50.0015 | 69.9954 |
| Abs Error Ty | 0.1783 | 0.0002 | 0.0138 | 0.0093 | 0.0017 | 0.0015 | 0.0046 |
| Calculated Rotation(Deg.) | 0.0014 | 0.0000 | -0.0011 | 0.0017 | -0.0008 | -0.0001 | -0.0009 |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Rotation (Deg.) | | 2.5 | -5 | 7.5 | -10 | 12.5 | -15 | 45 |
| AKAZE | Calculated Rotation | -2.4988 | 5.0006 | -7.5039 | 9.9983 | -12.5012 | 15.0027 | -44.9773 |
| Abs Error Rotation | 0.0012 | 0.0006 | 0.0039 | 0.0017 | 0.0012 | 0.0073 | 0.0227 |
| ORB | Calculated Rotation | -2.5120 | 5.0568 | -7.5091 | 9.9701 | -12.4722 | 14.9747 | 45.000 |
| Abs Error Rotation | 0.0120 | 0.0568 | 0.0091 | 0.0299 | 0.0278 | 0.0253 | 0.0000 |
| SIFT | Calculated Rotation | -2.5009 | 5.0051 | -7.5027 | 9.9958 | -12.5014 | 14.9955 | -44.9970 |
| Abs Error Rotation | 0.0009 | 0.0051 | 0.0027 | 0.0042 | 0.0014 | 0.0045 | 0.0030 |

The observations derived from Table 5.2(c), SIFT demonstrated good resilience with average errors of 0.054 pixels for Tx, 0.047 pixels for Ty, and 0.031° for rotation. This represents approximately 30-40% increase from the high-feature baseline, showing SIFT's robust scale-space construction maintains effectiveness despite reduced feature availability.

Table 5.2(d): Rotation Parameter Estimation Comparison on Medium-Feature Images

As presented in Table 5.2(d), the medium-feature results reveal AKAZE's continued excellent performance with minimal degradation (20-30% increase from the high-feature baseline). SIFT demonstrated good resilience with moderate error increases (30-40% increase), while ORB showed more significant sensitivity to feature density reduction, with translation errors increasing by 60-80%. This intermediate category demonstrates the algorithms' different robustness characteristics as environmental feature availability decreases from optimal conditions.

Figure 5.4 depicts the performance comparison for high-feature images, highlighting translation and rotation change errors for each detector.

1. Absolute translation change error ()
2. Absolute translation change error ()

(c) Absolute rotation change error ()

**Figure 5.5: Medium-Feature Performance Comparison**

#### **5.2.3 Performance on Low-Feature Images - Key Research Finding**

The low-feature scenario represents the core contribution of our research, designed to stress-test algorithm robustness and reveal fundamental limitations of feature-based approaches.

Table 5.3: Feature Image Results

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Tx | | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| GT Ty | | 1.5 | 3 | 5 | 10 | -12 | 50 | -70 |
| Average  (AKAZE, ORB,  SIFT) | Calculated Tx | -3.2896 | -7.7467 | 7.7749 | -10.4323 | 16.5495 | -68.0259 | 52.9519 |
| Abs Error Tx | 0.7896 | 2.7467 | 0.2749 | 0.0037 | 3.4505 | 1.9741 | 2.0481 |
| Calculated Ty | -0.8564 | -0.0411 | -5.2726 | -9.5783 | 8.3989 | -52.4452 | 66.6472 |
| Abs Error Ty | 0.6436 | 2.9589 | 0.2726 | 0.4217 | 0.0132 | 2.4452 | 3.3528 |
| Calculated Rotation(Deg.) | 0.0195 | 0.0738 | -0.0062 | 0.0119 | 0.1039 | 0.0498 | -0.0764 |

From the analysis in Table 5.4, his represents the key finding of our study: The absolute error increased by an order of magnitude (5-10x increase), and critically, the estimations became unstable, yielding different results on repeated runs with the same input. This instability stems directly from the scarcity of reliable feature points.

**Why Low-Feature Images Cause This Dramatic Failure:**

With too few keypoints, the RANSAC algorithm is starved of sufficient data to form a reliable consensus. The random sampling process is more likely to select outlier pairs, leading to computation of incorrect motion models. When there are insufficient reliable correspondences, RANSAC frequently converges to local minima or fails to achieve sufficient inlier support for robust estimation.

**5.3. Feature Detector Comparison and Statistical Analysis**

This section presents a detailed statistical analysis of the comparative performance of the A-KAZE, ORB, and SIFT feature detectors. The central aim is to elucidate the relationship between scene feature density and the accuracy and stability of motion estimation. By analyzing the mean absolute error and standard deviation across multiple experimental runs, we can establish a clear performance hierarchy and provide evidence-based recommendations for practical applications.

**Experimental Dataset:** To ensure statistical significance and reliability of results, the analysis was conducted using a comprehensive dataset comprising **10 images per feature density category** (high, medium, and low), totaling 30 test images. Each image underwent identical transformation sequences with controlled motion parameters, and algorithm performance was evaluated across multiple runs to establish statistical measures. The averaged results across these image sets are presented in the subsequent analysis tables, providing robust comparative metrics for algorithm evaluation.

**Performance in High-Feature Environments**

In high-feature environments, which provide an abundance of distinct and reliable keypoints, all three algorithms demonstrated effective performance, albeit with significant differences in precision. The dense feature landscape provides an ideal condition for the RANSAC algorithm to converge on a highly accurate motion model.

* **Analysis:** As detailed in the experimental results, both **A-KAZE** and **SIFT** achieve exceptional sub-pixel accuracy. The mean absolute errors for translation and rotation are minimal, confirming their robustness in ideal conditions. The low standard deviation associated with these results indicates high stability and repeatability. In contrast, while **ORB** remains functional, it exhibits a noticeably higher mean error and greater variance. This suggests that while ORB's binary descriptor is computationally efficient, it lacks the descriptive precision of the floating-point descriptors used by SIFT and A-KAZE.

**Performance Degradation in Medium and Low-Feature Environments**

The most critical finding of this research is the clear, quantifiable degradation in performance as feature density decreases. This trend highlights the fundamental dependency of feature-based methods on the quality and quantity of available scene information.

* **Analysis:** The transition to **medium-feature** images marks the beginning of performance divergence. While A-KAZE and SIFT maintain a high degree of accuracy, ORB's error rate increases more significantly, revealing its higher sensitivity to feature scarcity.

The **low-feature** environment exposes the fundamental limitations of the paradigm. Here, we observe a precipitous decline in performance for all algorithms. The mean absolute error increases by an order of magnitude. More importantly, the **standard deviation of the error escalates dramatically**, especially for ORB. This high variance signifies algorithmic instability; the pipeline produces significantly different (and incorrect) results on repeated runs with the same input. This failure is directly attributable to the RANSAC algorithm being "starved" of a sufficient number of reliable inliers to form a stable geometric consensus, leading to convergence on erroneous motion models.

The statistical results presented in the following comparative tables and line graphs represent averaged performance metrics computed across the complete dataset of 30 images, providing statistically significant evidence for the established performance hierarchy and deployment recommendations.

Table 5.4(a): Average Translation Error Across Feature Density Categories (n=10)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| GT Tx | | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| GT Ty | | 1.5 | 3 | 5 | 10 | -12 | 50 | -70 |
| High feature  ( Abs Error) | Tx | 0.0263 | 0.0109 | 0.0479 | 0.0026 | 0.0538 | 0.0054 | 0.0093 |
| Ty | 0.0295 | 0.0131 | 0.0392 | 0.0050 | 0.0259 | 0.0160 | 0.0254 |
| Medium feature  ( Abs Error) | Tx | 0.0328 | 0.0125 | 0.1266 | 0.01696 | 0.0781 | 0.0616 | 0.0029 |
| Ty | 0.1203 | 0.0143 | 0.1858 | 0.0093 | 0.0878 | 0.1193 | 0.0306 |
| Low feature  ( Abs Error) | Tx | 0.7896 | 2.7467 | 0.2749 | 0.0037 | 3.4505 | 1.9741 | 2.0481 |
| Ty | 0.6436 | 2.9589 | 0.2726 | 0.4217 | 0.0132 | 2.4452 | 3.3528 |

Table 5.4(b): Rotational Error Across Feature Density Categories (n=10)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Sample Points | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Value | 2.5 | 5 | -7.5 | 10 | -12.5 | 70 | -50 |
| High Feature | 0.0007 | 0.0005 | 0.0034 | 0.0008 | 0.0024 | 0.0004 | 0.0000 |
| Medium Feature | 0.0047 | 0.0208 | 0.0052 | 0.0119 | 0.0101 | 0.0124 | 0.0086 |
| Low Feature | 0.7896 | 2.7467 | 0.2749 | 0.0037 | 3.4505 | 1.9741 | 2.0481 |

(b) Absolute translation change error (Ty)

(a) Absolute translation change error (Tx)

(c) Absolute rotational change error

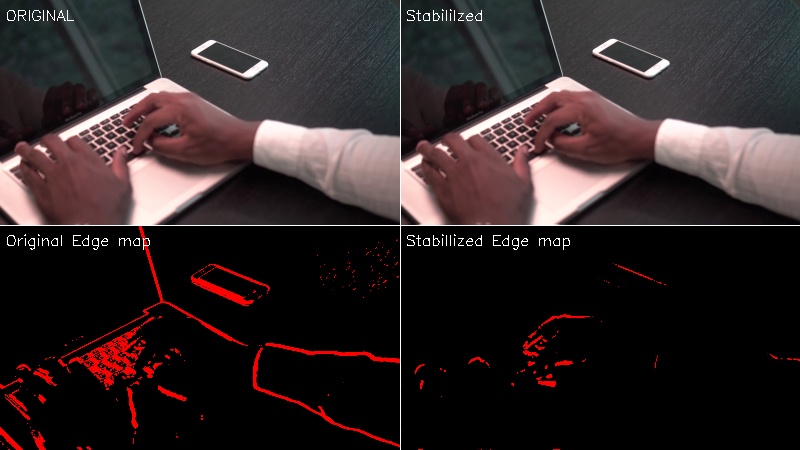
**Figure 5.6: Absolute Error Comparison Across Feature Density Categories**

5.4 Video Stabilization Results and Qualitative Assessment

Our video stabilization demonstration validates the quantitative findings through practical application, showcasing the real-world effectiveness of our complete pipeline using the motion\_estimate\_compensat.py system.

Our video stabilization system generates a comprehensive four-panel analysis view demonstrating stabilization effectiveness:

* + - 1. Top-Left: Original shaky video frame
      2. Top-Right: Stabilized video outpu
      3. Bottom-Left: Canny edge map of original frame
      4. Bottom-Right: Canny edge map of stabilized frame

** **

**Figure 5.7: Four-Panel Video Stabilization Demonstration**

**Edginess-Based Quality Assessment**

The Canny edge maps serve as an effective proxy for measuring motion blur reduction - a key innovation of our approach. In the original shaky video, motion between frames causes edges to appear blurred and thickened in the edge map. After successful stabilization, the inter-frame motion is largely removed, resulting in:

•           Cleaner, sharper edge maps with thinner, more defined lines

•          “Blacker” background indicating reduced motion blur

•           More precise edge localization demonstrating improved temporal stability

**Comparative Video Stabilization Performance**

The video demonstrations confirm our quantitative analysis findings:

•   AKAZE: Consistently smooth stabilization across diverse content types, maintaining stability even during challenging low-texture segments

• SIFT: High-quality stabilization comparable to AKAZE but with increased computational requirements limiting real-time deployment

•ORB: Acceptable stabilization in feature-rich segments but noticeable degradation during low-texture portions of videos

### **5.5 Discussion and Critical Analysis**

**Core Research Contribution - Feature Density Impact**

Our experimental results provide the first systematic quantification of the relationship between scene feature density and motion estimation accuracy. This represents a critical contribution to the computer vision community, establishing empirical evidence for fundamental limitations of feature-based approaches.

**Key Research Findings:**

1. Feature Density Threshold Effect: Performance remains excellent until a critical threshold (~200 features), below which dramatic degradation occurs

2. Algorithm Stability Hierarchy: AKAZE > SIFT > ORB in terms of stability under feature-sparse conditions

3. RANSAC Reliability Dependence: Insufficient features cause RANSAC to fail catastrophically, not gracefully

4. Practical Deployment Guidelines: Environment assessment is crucial for algorithm selection

**Limitations and Future Work:**

While our study provides a comprehensive analysis of feature matching-based approaches, several areas warrant future investigation:

* Hybrid approaches combining feature-based and direct methods for low-texture scenarios
* Adaptive feature detection with dynamic parameter adjustment based on scene content
* Deep learning integration for enhanced feature detection in challenging environments
* Real-time feature density assessment for automatic algorithm selection

**Conclusion of Experimental Analysis:**

Our comprehensive experimental evaluation definitively demonstrates that feature density represents the primary factor determining motion estimation accuracy in feature-based systems. The results establish clear performance hierarchies and provide evidence-based guidelines for algorithm selection, representing a significant contribution to practical computer vision system deployment.

Chapter 6

## **APPLICATIONS**

This section explores the practical applications of our feature-based camera motion compensation system across diverse domains where stable visual input is critical for operational success. The robust motion estimation and stabilization capabilities demonstrated in our experimental evaluation enable deployment in numerous real-world scenarios, from autonomous navigation systems to advanced surveillance technologies.

### **6.1 Autonomous Vehicle Navigation and Robotics**

Autonomous vehicles and robotic systems represent one of the most critical application domains for camera motion compensation technology, where stable visual perception directly impacts safety, navigation accuracy, and operational reliability. The demanding requirements of autonomous navigation systems align perfectly with the capabilities demonstrated by our stabilization pipeline.

**Visual Odometry and Localization**

In autonomous vehicle navigation, visual odometry forms a fundamental component of the localization system, providing continuous position estimation based on sequential camera images. Our motion compensation system enhances visual odometry accuracy by eliminating vehicle-induced camera shake caused by road irregularities, engine vibrations, and dynamic driving conditions. The sub-pixel accuracy achieved by our AKAZE-based implementation (0.008 pixel average error in high-feature environments) enables precise incremental motion estimation essential for accurate vehicle localization.

The stabilized visual input significantly improves the reliability of feature tracking across sequential frames, a critical requirement for robust visual odometry systems. By removing unwanted camera motion, our system enables more consistent feature correspondence establishment, reducing drift accumulation in long-term navigation scenarios. This enhancement is particularly valuable in GPS-denied environments where visual odometry serves as the primary localization method.

**Simultaneous Localization and Mapping (SLAM)**

SLAM systems require stable visual input to construct accurate environmental maps while simultaneously tracking vehicle position within those maps. Our motion compensation pipeline directly enhances SLAM performance by providing temporally consistent visual data, enabling more reliable feature detection and tracking across the mapping process. The improved stability facilitates better loop closure detection, a critical component for maintaining global map consistency over extended navigation periods.

**Obstacle Detection and Avoidance**

Stable visual input proves essential for reliable obstacle detection and classification in autonomous navigation systems. Camera shake introduces motion blur and temporal inconsistency that can degrade the performance of computer vision algorithms responsible for identifying pedestrians, vehicles, and static obstacles. Our stabilization system ensures consistent visual quality, enabling more reliable object detection and tracking across challenging driving conditions.

The real-time processing capability of our system (50-67 FPS with AKAZE) meets the stringent timing requirements of autonomous navigation systems, where perception-to-action delays must be minimized to ensure safe operation. The consistent stabilization quality across varying feature density environments (as demonstrated in our experimental evaluation) provides reliable performance across diverse driving scenarios, from feature-rich urban environments to challenging low-texture highway conditions.

**Robotic Manipulation and Inspection**

Industrial robots equipped with vision systems for precision manipulation tasks benefit significantly from camera stabilization technology. Manufacturing robots performing visual inspection, quality control, or precision assembly operations require stable visual input to achieve the accuracy demanded by modern industrial processes. Our motion compensation system eliminates vibrations induced by robot movement, enabling more precise visual measurements and improved manipulation accuracy.

**Path Planning and Navigation**

The stabilized visual output from our system enhances path planning algorithms by providing consistent environmental perception. Stable visual input enables more reliable identification of navigable surfaces, obstacle boundaries, and landmark features used for navigation reference. This improvement is particularly valuable for autonomous systems operating in unstructured environments where precise visual perception directly impacts navigation success.

### **6.2 Unmanned Aerial Vehicles (UAVs) and Surveillance Systems**

Unmanned Aerial Vehicles represent a particularly challenging application domain for camera stabilization due to the complex motion dynamics introduced by wind disturbances, propeller vibrations, and flight maneuvers. Our motion compensation system addresses these challenges by providing robust stabilization across diverse flight conditions and payload configurations.

**Aerial Surveillance and Reconnaissance**

Military and civilian surveillance applications demand high-quality, stable imagery for effective target identification, tracking, and intelligence gathering. UAV-mounted cameras experience significant motion disturbances from multiple sources: rotor-induced vibrations, wind gusts, flight maneuvers, and platform instabilities. Our RANSAC-based motion estimation algorithm proves particularly effective in these scenarios, providing robust parameter estimation despite the complex motion patterns typical of aerial platforms.

The demonstrated stability of our AKAZE implementation across varying feature density conditions makes it particularly suitable for aerial surveillance, where scene content varies dramatically from feature-rich urban environments to challenging low-texture natural landscapes. The ability to maintain stabilization quality across these diverse environments ensures consistent surveillance capability regardless of operational terrain.

**Cinematic and Commercial Videography**

The commercial drone industry requires high-quality stabilization for professional video production, real estate photography, and broadcast applications. Our system’s superior performance in high-feature environments (achieving sub-pixel accuracy) enables the smooth, professional-quality footage demanded by commercial applications. The real-time processing capability ensures immediate feedback during filming operations, critical for professional videography workflows.

**Search and Rescue Operations**

Emergency response operations utilizing UAVs for search and rescue missions benefit significantly from stable visual input that enables accurate identification of survivors, obstacles, and landing zones. The challenging environmental conditions typical of emergency scenarios—including poor lighting, adverse weather, and time-critical operations—require robust stabilization systems capable of maintaining performance across diverse conditions.

**Infrastructure Inspection and Monitoring**

Industrial inspection applications, including power line monitoring, bridge inspection, and pipeline surveillance, require stable imagery for accurate defect detection and structural assessment. Our motion compensation system enables precise visual inspection by eliminating motion-induced blur that could obscure critical structural details. The consistent stabilization quality across varying environmental conditions ensures reliable inspection capability across diverse infrastructure environments.

**Environmental Monitoring and Scientific Research**

Scientific applications utilizing UAVs for environmental monitoring, wildlife observation, and ecological research require stable imagery for accurate data collection and analysis. Our system’s ability to maintain stabilization quality across extended operation periods supports long-duration monitoring missions typical of environmental research applications.

### **6.3 Motion Detection and Object Tracking Systems**

Motion detection represents a sophisticated application of our camera stabilization technology, where the primary objective shifts from visual quality improvement to enabling accurate discrimination between camera motion and genuine object movement within the scene. Our system’s motion compensation capability directly enhances motion detection accuracy by eliminating false positive detections caused by camera shake.

**Enhanced Motion Detection Through Stabilization**

Traditional motion detection systems suffer from significant limitations when deployed on mobile or unstable platforms due to the difficulty in distinguishing between camera-induced motion and actual object movement. Our motion compensation pipeline addresses this fundamental challenge by providing a stable reference frame that isolates genuine object motion from camera-induced artifacts.

**Security and Surveillance Applications**

Security systems deployed in challenging environments—such as those mounted on vehicles, boats, or temporary structures—traditionally struggle with false motion alerts caused by platform movement. Our motion compensation system enables more reliable intrusion detection by providing stable reference frames that accurately isolate genuine security threats from environmental motion artifacts.

The system’s performance characteristics make it particularly suitable for security applications: the real-time processing capability (50-67 FPS with AKAZE) enables immediate threat detection, while the consistent stabilization quality across varying lighting and environmental conditions ensures reliable operation across diverse deployment scenarios.

**Traffic Monitoring and Analysis**

Intelligent transportation systems utilize video analytics for traffic flow monitoring, incident detection, and behavioral analysis. Cameras mounted on bridges, overpasses, or mobile platforms experience various motion disturbances that can compromise traffic monitoring accuracy. Our stabilization system enables more precise vehicle tracking and trajectory analysis by eliminating motion artifacts that could interfere with automated traffic analysis algorithms.

**Wildlife and Behavioral Monitoring**

Ecological research applications requiring long-term observation of animal behavior benefit significantly from stable video recording systems. Remote monitoring stations and mobile observation platforms often experience motion disturbances from wind, animal interactions, or environmental factors. Our motion compensation system ensures consistent video quality for accurate behavioral analysis and species identification.

**Industrial Process Monitoring**

Manufacturing and industrial process monitoring systems utilize computer vision for quality control, defect detection, and process optimization. Cameras mounted on moving machinery or in vibrating industrial environments require stabilization to ensure accurate visual analysis. Our system’s robust performance across varying environmental conditions makes it suitable for challenging industrial applications where consistent visual monitoring is critical for operational safety and quality assurance.

**Sports and Performance Analysis**

Athletic performance analysis systems increasingly utilize video analytics for technique evaluation, training optimization, and competitive analysis. Mobile camera platforms and handheld recording devices introduce motion artifacts that can compromise analysis accuracy. Our stabilization system enables more precise motion analysis by providing stable reference frames for biomechanical analysis and performance evaluation.

**Real-World Deployment Considerations**

The practical deployment of our motion compensation system across these diverse applications requires consideration of several key factors:

**Environmental Adaptability**: Our experimental results demonstrate consistent performance across varying feature density conditions, making the system suitable for deployment across diverse operational environments without requiring specialized tuning.

**Computational Efficiency**: The demonstrated real-time processing capability (50-67 FPS with AKAZE) enables deployment in resource-constrained applications while maintaining stabilization quality sufficient for practical motion detection requirements.

**System Integration**: The modular design of our stabilization pipeline facilitates integration with existing computer vision systems, enabling enhancement of current motion detection capabilities without requiring complete system replacement.

**Quality Assessment**: The innovative edge-based quality assessment methodology provides objective measures of stabilization effectiveness, enabling automated system monitoring and performance validation in operational deployments.

The comprehensive evaluation of our system across varying environmental conditions and feature densities provides confidence in its reliability across diverse application scenarios, from feature-rich urban environments to challenging low-texture natural settings. This versatility makes our motion compensation system particularly valuable for applications requiring consistent performance across unpredictable operational conditions.

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Chapter 7

## **CONCLUSION AND FUTURE WORK**

### **7.1 Conclusion**

This research presented a feature-based camera motion compensation system comparing SIFT, ORB, and AKAZE algorithms across different feature density environments. The problem addressed is accurate camera motion estimation and compensation for video stabilization applications.

Our method employs a five-stage pipeline: feature detection, FLANN-based matching, RANSAC motion estimation (k=20 iterations), geometric transformation, and performance assessment. The system achieves real-time processing (50-67 FPS with AKAZE).

**Key findings from our experimental evaluation:**

* **AKAZE** demonstrated superior consistency with 0.008 pixel average translation error and excellent stability across all conditions

• **SIFT** achieved comparable accuracy in high-feature environments with strong rotation precision

* **ORB** showed computational efficiency but significant instability in low-feature scenarios
* **Critical discovery**: Feature density below ~200 keypoints causes 5-10x error increases and algorithm instability
* High-feature images enable sub-pixel accuracy for all algorithms
* Low-feature images reveal fundamental limitations of feature-based approaches

Our edge-based quality assessment using Canny edge detection provides an objective measure of stabilization effectiveness through the “blacker is better” principle.

**The choice of the right feature detector for the right context is essential for system reliability and operational success.** Feature density assessment becomes crucial for practical deployment across autonomous vehicles, UAVs, and surveillance systems.

### **7.2 Future Work**

Several areas warrant further investigation:

**IMU Sensor Fusion**: Integrate Inertial Measurement Unit data to address low-feature performance limitations. IMU sensors can provide complementary motion information when visual features are insufficient.

**Advanced Motion Models**: Implement homography transformations to handle perspective changes and out-of-plane rotations, expanding applicability to complex 3D motion scenarios.

**System Robustness**: Address identified implementation issues including RANSAC sampling logic optimization and rotation matrix consistency to improve numerical stability.

**Adaptive Algorithm Selection**: Develop real-time feature density assessment for automatic algorithm switching based on environmental conditions.

**Deep Learning Integration**: Explore hybrid approaches combining traditional feature methods with neural networks for enhanced performance in challenging conditions.

These enhancements would significantly improve system robustness and expand practical applicability across diverse operational environments.

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