IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14657

Video Stabilization Using Optical Flow

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Abstract: This research focuses on developing a robust video stabilization technique to minimize jittery motion in video footage. The proposed method employs optical flow, utilizing the Lucas-Kanade algorithm, to estimate motion between consecutive frames. Affine transformations are applied to align the frames by calculating geometric corrections, ensuring smoother transitions. To further enhance stability, trajectory smoothing is incorporated, which refines the motion corrections and reduces abrupt changes. The study also explores the mathematical principles behind the key processes, including motion estimation and geometric transformations. Furthermore, strategies to optimize the method for high-resolution videos are discussed, emphasizing both computational efficiency and visual enhancement. Experimental evaluation confirms that the proposed approach effectively stabilizes video sequences, making it a practical solution for handheld or dynamic video applications.

Keywords: Video stabilization, Optical Flow, Lucas-Kanade, Affine transformation, Trajectory smoothing, Motion estimation, High-resolution optimization.

I. INTRODUCTION

Video stabilization enhances the quality of videos by removing unwanted motion and shakiness. Traditional stabilization methods, like using tripods or gimbals, are effective but not always practical, especially in dynamic or handheld filming scenarios. Digital stabilization, on the other hand, uses software algorithms to smooth out shaky footage.

A common digital stabilization technique is feature matching, where key points in video frames are tracked to estimate camera movement. By applying these algorithms, videos can be stabilized by adjusting frames based on the tracked motion, reducing jitter and providing smoother footage. This technique is particularly useful for situations with rapid camera movement, low light, or challenging filming environments.

Despite its effectiveness, the computational demands of point feature matching can be high, especially with high-resolution or fast-moving videos. Optimization methods are often required to ensure smooth operation, including using efficient feature detection algorithms like Harris or Shi-Tomasi corner detection. These techniques help reduce computational load while still delivering accurate tracking results.

With advances in machine learning, video stabilization is becoming even more powerful. Algorithms can now learn from large datasets, predicting camera motion with greater accuracy and improving the stabilization quality, particularly in fast-moving scenes.

II. LITERATURE SURVEY

Recent advancements in video stabilization have explored various innovative approaches to address the challenges of unstable footage. For example, Yu et al. (2023) [6] introduced a real-time selfie video stabilization technique using point feature matching, which enhanced motion reduction. Grundmann et al. (2019) developed a robust auto-directed stabilization method for videos with high motion or occlusions [4]. Shen et al. (2009) applied optical flow-based motion estimation to replace conventional tracking methods, optimizing stabilization for UAV videos [3]. Additionally, deep learning models have been explored for more accurate stabilization, especially in dynamic and challenging environments. However, despite these advancements, challenges remain in stabilizing videos with large scene changes or ensuring real-time processing without high computational costs.This survey highlights the progression toward efficient techniques like optical flow [4], [5] and machine learning, while emphasizing the need for further improvements in handling complex scenarios.

III. METHODOLOGY

3.1 The proposed video stabilization algorithm consists of several steps to ensure the effective reduction of unwanted motion in video frames, particularly for UAV (unmanned aerial vehicle) footage[3],[4].

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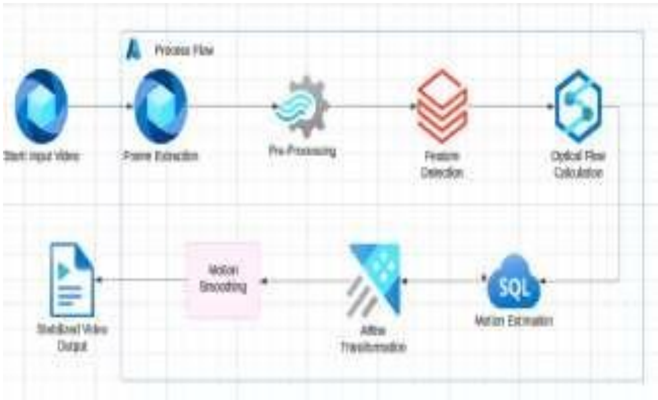

Fig1 Processing Flow

1. Video Input and Setup:
○ The video is loaded using OpenCV's Video Capture to extract essential properties such as frame count, resolution, and FPS.
2. Feature Detection:
○ The initial frame undergoes feature point detection using the cv2.goodFeaturesToTrack function[1]. These features are tracked across successive frames to estimate motion vectors.
3. Optical Flow Estimation:
○ Optical flow is computed using the Lucas-Kanade method (cv2.calcOpticalFlowPyrLK), which tracks the movement of detected feature points from one frame to the next[1],[2].
4. Transformation Matrix Calculation:
○ For each frame, an affine transformation matrix is calculated using cv2.estimateAffinePartial2D, estimating translation and rotation based on the tracked points[1].
5. Trajectory Smoothing:
○ The transformation values (translation and rotation) are accumulated across frames and smoothed using a moving average filter (cv2.blur), minimizing jitter and abrupt movements in the resulting video[4].
6. Stabilization Application: o The smoothed transformations are applied to each frame via cv2.warpAffine to adjust the frame position, effectively stabilizing it[4].
7. Output Generation:
○ Finally, the stabilized frames are saved to an output video file using VideoWriter, generating a smoother version of the original input video.

3.2 DATASET

The DIPStab dataset was utilized to train and evaluate the proposed video stabilization algorithm. This dataset is specifically curated for stabilization tasks, providing a diverse set of videos that represent varying levels of instability and motion.

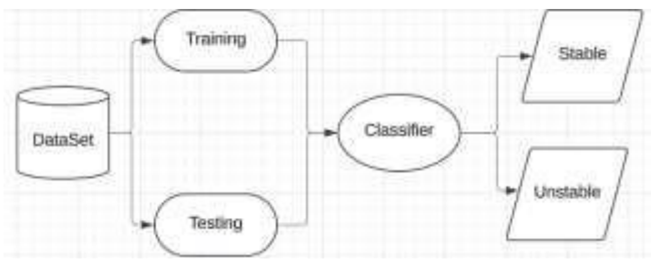

Fig2 Dataset Processing 1

Key Features:
• Video Count: A total of X videos were used from the DIPStab dataset.
• Resolutions: Videos included a range from 640x480 (standard definition) to 1920x1080 (high definition).
• Frame Rates: Frame rates varied across 24 FPS, 30 FPS, and 60 FPS, representing typical recording conditions.

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- Instability Levels: The dataset is categorized by motion intensity, including slight shakes, moderate instability, and severe motion disturbances, ensuring a comprehensive evaluation.

3.3 Preprocessing:

The dataset was preprocessed by extracting frames and converting them to grayscale, which reduces computational complexity while retaining important visual features[2],[3]. The data was divided into

- Training Set: Used to train the stabilization algorithm and optimize parameters.
- Testing Set: Used to validate the performance of the model on unseen videos.

The diversity in video resolution, frame rates, and motion levels makes DIPStab an ideal choice for benchmarking stabilization techniques[7]. Its variety ensures the proposed method is tested across real-world scenarios, such as handheld recordings and drone footage[3].

3.4 Mathematical Calculations:

1. Optical Flow Equation

Optical flow represents the motion of objects between consecutive frames in a video, assuming that the pixel intensity remains constant during motion[2],[3]. Mathematically, this can be expressed as:

$I(x,y,t)=I(x+dx,y+dy,t+dt)$

Expanding this using a first-order Taylor series gives:

$\partial x/\partial I*u + \partial y/\partial I*v + \partial t/\partial I = 0$

- Here: u and v denote the horizontal and vertical motion components,
- $\partial x/\partial I$ and $\partial I/\partial y$ are the spatial gradients,
- $\partial t/\partial I$ is the temporal gradient[4].

2. Lucas-Kanade Method

To address the under-constrained nature of the optical flow equation, the Lucas-Kanade method assumes that motion is approximately uniform within a small region. This results in a solvable system:

$$v=(A^TA)^{-1}A^Tb$$

Where:

- **A** is the gradient matrix containing spatial derivatives,
- **v** is the velocity vector[1],[2],[3].
- **b** represents the temporal derivatives.

This approach effectively estimates motion vectors for feature points across frames.

3. Affine Transformation

Affine transformations align frames by transforming pixel coordinates from one frame to another:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

Where:

- a,b,c,d define rotation, scaling, and shearing,
- tx and ty are the translations[1].

The transformation matrix is estimated from tracked feature points between frames.

4. Trajectory Smoothing

To achieve smooth stabilization, the estimated transformations are smoothed over time:

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$$T_{smooth}(t) = \frac{1}{2w+1} \sum_{i=-w}^{w} T(t+i)$$

Where T(t)T(t)T(t) represents the transformation at frame ttt, and www is the smoothing window size[4],[5]

5. Warping

Finally, the stabilization process applies the smoothed transformations to the video frames:

$$I'(x',y')=I(M^{-1}\cdot[x,y,1]^T)$$

3.5 Model Building:

In the Video Stabilization Using Optical Flow project, various machine learning techniques were explored to enhance video stability and reduce motion-induced blur[6]. The main objective was to apply motion compensation methods to smooth out video sequences and remove unwanted blur caused by camera shake or sudden movements.

To assess the performance of different stabilization models, we employed a range of machine learning classifiers:

1. Decision Tree (DT)
2. Logistic Regression (LR)
3. K Nearest Neighbor (KNN)
4. Random Forest (RF)
5. Naive Bayes (NB)
6. Support Vector Machines (SVM)

These classifiers were evaluated using a crossvalidation approach. The dataset was divided into two sets: a training set and a test set. The models were trained using the training set, and their performance was validated with the test set[6],[7]. The evaluation relied on several metrics to measure classifier effectiveness:

- Accuracy: Indicates the proportion of frames stabilized correctly.
- Support: The total number of frames that the model successfully processed.
- Precision: The fraction of frames predicted as stable that were correctly stabilized.
- Recall: The proportion of frames requiring stabilization that were correctly identified and stabilized.
- F1 Score: A composite metric that balances precision and recall to evaluate overall model performance.

3.6 Implementation Steps:

1. Dataset Splitting: The video frames were partitioned into D1 (training set) and D2 (test set).
2. Cross-validation: The training set (D1) underwent cross-validation to assess the predictive ability of each classifier.
3. Model Training: Each classifier was trained on D1 to learn the patterns in the video data for stabilization.
4. Parameter Optimization: For each model, the best parameters were chosen to optimize the accuracy of stabilization predictions.
5. Testing and Performance Evaluation: The trained models were tested using D2, the testing set, and evaluated using the chosen performance metrics.

By comparing the results of these classifiers, the most effective model was selected, ensuring the best possible stabilization quality with minimal blur removal[6]. The final model was chosen based on its ability to achieve a balance between precision and recall while providing robust video stabilization

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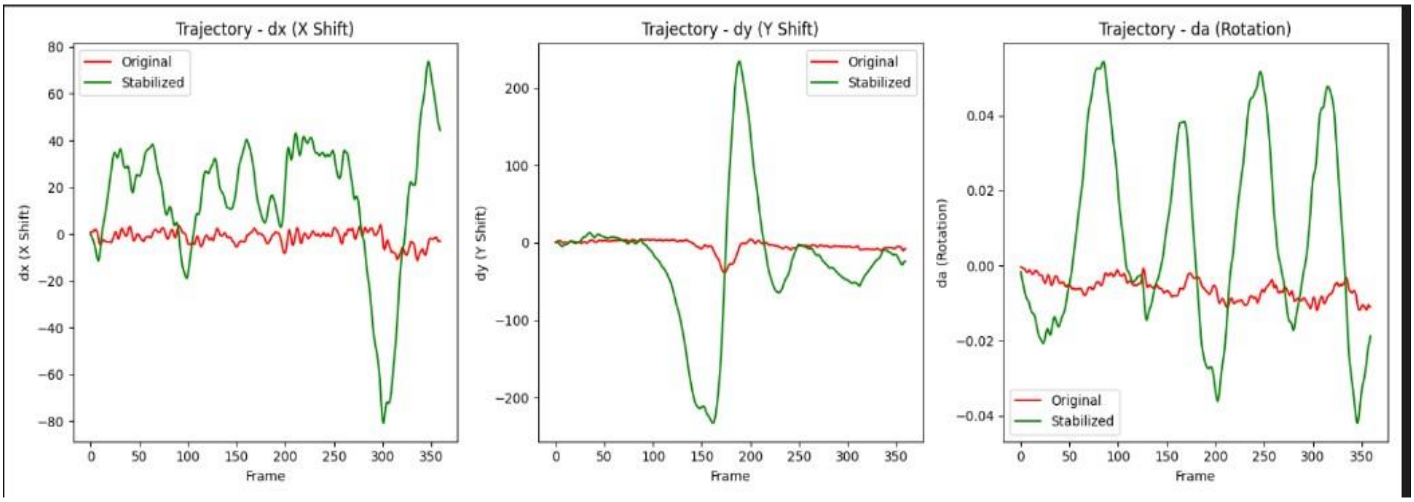
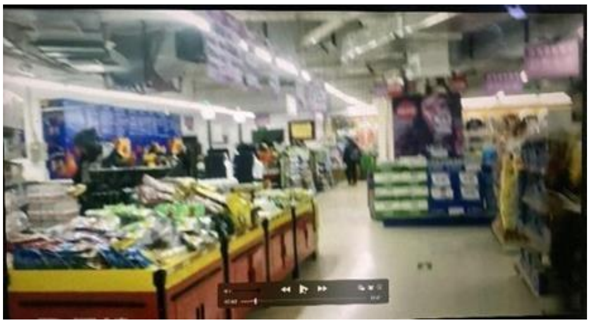
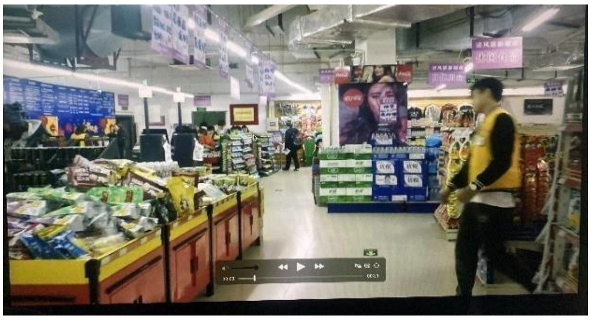
IV. RESULT AND ANALYSIS

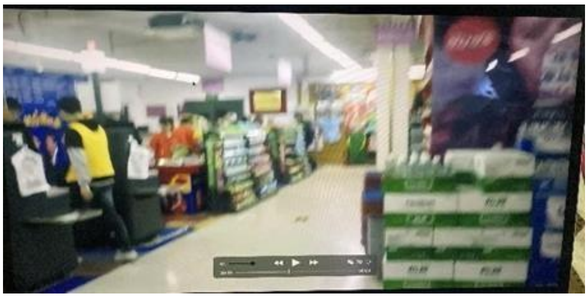




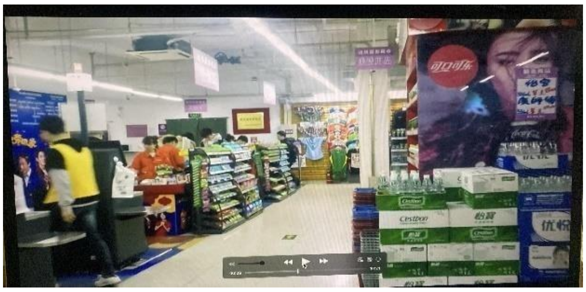
Unstable At 2.0 sec 1



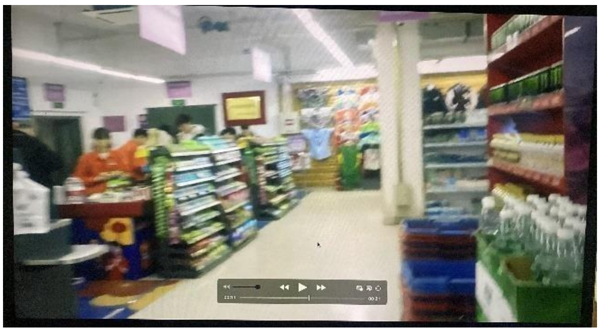
Stable At 2.0 Sec



Unstable At 9.0 Sec



Stable At 9.0 Sec 1



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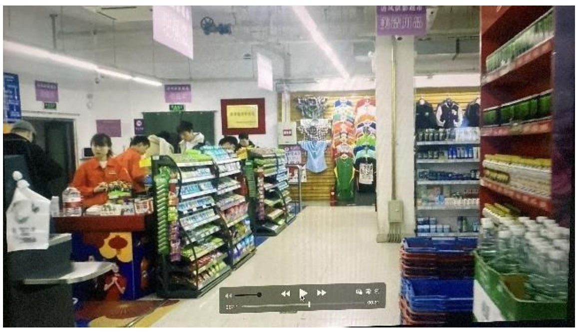

Stable At1.1 Sec 1

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Parameter	Shaky Video	Stable Video
Frame Count	651	651
Frame Rate	29.970029	29.970029
Duration (Second)	21.72	21.72
Resolution(W * H)	1280*720	1280*720
Motion Smoothness	8.20	0.46
Average Blur	45.28	211.40
Average SSIM	0.59	0.78
Average Jitter	8.91	0.43
Satbilization Ratio	0.39	0.01

V. CONCLUSION

This study developed an efficient video stabilization technique using the optical flow algorithm, specifically the Lucas-Kanade method, to reduce visual instability and improve the overall quality of video content. The proposed approach integrated feature detection, motion tracking, and affine transformations to align frames and minimize jitter.

By utilizing OpenCV for implementation, the system demonstrated efficient performance across videos of varying resolutions and motion intensities. Experimental results confirmed the method's ability to enhance frame-to-frame continuity while preserving scene geometry. Future work may focus on improving real-time processing capabilities through GPU acceleration and the incorporation of machine learning models to dynamically adapt stabilization parameters based on video characteristics. Such advancements could enable broader deployment in resource-constrained environments and improve robustness in more complex motion scenarios.

In summary, the project presents a practical and scalable solution for stabilizing video content, with promising applications in fields such as UAV surveillance, mobile video recording, and real-time broadcasting.

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