

# BasicFlow: Lightweight SteadyFlow-Based Video Stabilization

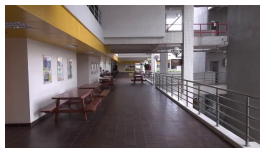
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CS7.404 Digital Image Processing

# Introduction & Problem Statement

- Videos often suffer from jitter, wobble, parallax effects, and distortions due to handheld motion or scene depth changes.
- Video stabilization aims to correct these issues by estimating camera motion and producing a smoother visual trajectory between frames.
- SteadyFlow achieves high-quality stabilization by creating a spatially coherent optical flow, allowing us to smooth pixel profiles rather than feature trajectories.
- Our method, BasicFlow, provides a lightweight alternative by using RAFT flow, simple spatial masking, and efficient temporal smoothing.

# Optical Flow

**Optical Flow** describes the apparent motion of pixels between two consecutive video frames. It provides a 2D motion vector  $(u, v)$  at each pixel, indicating how that pixel has moved.



Original Frame

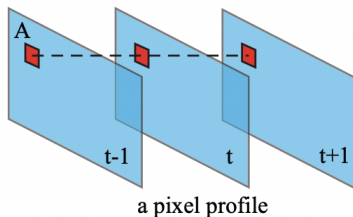
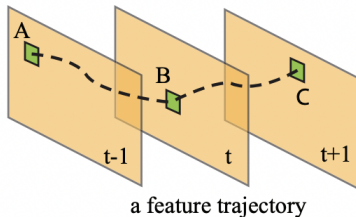


Initial Optical Flow



BasicFlow

# Feature Trajectories vs Pixel Profiles



- **Feature trajectories** track the motion of specific feature points across frames, but can break if features disappear or move out of view.
- **Pixel profiles** track the motion at the same pixel location over time, providing dense and stable information for every pixel.

# Traditional Methods & Their Limitations

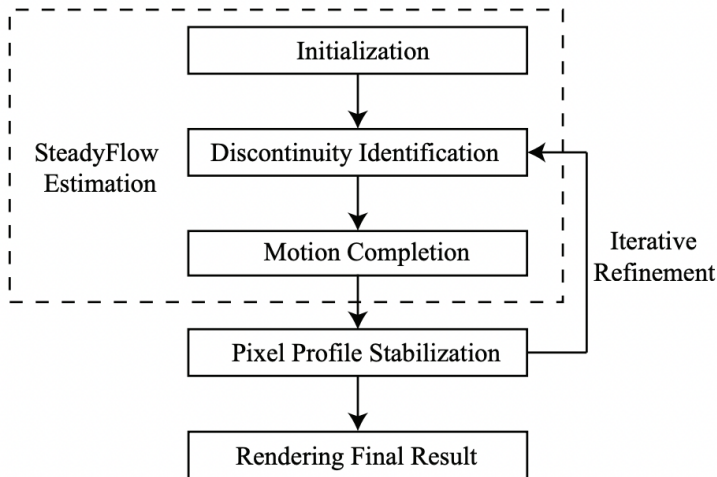
- Traditional stabilization uses global 2D models like affine or homography to approximate camera motion.
- These models assume the entire scene moves rigidly, which fails in the presence of depth variation or parallax.
- Feature-based tracking can be unreliable when features disappear, drift, or become unevenly distributed.
- Dynamic objects introduce inconsistent motion that global models cannot represent.
- As a result, traditional methods often produce wobble, distortion, or over-smoothing in complex scenes.

- SteadyFlow is a dense-flow video stabilization method designed to handle spatially-varying motion such as parallax and depth changes.
- Instead of relying on sparse feature trajectories, it analyzes pixel-wise motion across time using **pixel profiles**.
- The core idea is to build a spatially smooth optical flow field and then temporally smooth each pixel's motion to obtain a stable camera path.

# SteadyFlow: The Process

- **1. Initialization:** Estimate dense optical flow and a global homography to capture coarse camera motion.
- **2. Discontinuity Identification:** Detect unreliable flow regions using spatial gradients and temporal inconsistency.
- **3. Motion Completion:** Fill in missing or inconsistent flow using mesh-based as-similar-as-possible warping to enforce spatial smoothness.
- **4. Pixel Profile Stabilization:** Build motion profiles for each pixel across time and smooth them using temporal optimization.
- **5. Iterative Refinement:** Repeat discontinuity detection and completion until the flow field becomes stable.

# SteadyFlow Pipeline



- Iteratively refines discontinuous flow into a smooth field.
- Stabilizes the video by smoothing pixel motion profiles.



- MeshFlow is a lightweight, online video stabilization method that replaces dense flow with a **sparse mesh-based motion model**.
- Instead of computing dense pixel motion, it tracks sparse features and propagates their motion to mesh vertices.
- Two median filters remove outliers and enforce spatial smoothness across the mesh.
- It avoids SteadyFlow's heavy flow refinement and ASAP motion completion.
- Predicts stabilization strength using PAPS (Predicted Adaptive Path Smoothing), removing the iterative search used by SteadyFlow.

# Smoothing Formulas

## SteadyFlow

$$E(P) = \sum_t \left( \|P(t) - C(t)\|^2 + \lambda_t \sum_r w_{t,r} \|P(t) - P(r)\|^2 \right)$$

## MeshFlow (PAPS)

$$\lambda_t = \max\left(0, \min(\lambda_t^{(1)}, \lambda_t^{(2)})\right)$$

$$\lambda_t^{(1)} = -1.93 T_v + 0.95, \quad \lambda_t^{(2)} = 5.83 F_a + 4.88$$

*PAPS predicts the same smoothing weight  $\lambda_t$  used in the SteadyFlow energy, but estimates it directly from translation magnitude ( $T_v$ ) and affine deformation ( $F_a$ ), instead of performing SteadyFlow's slow iterative search.*

# What is BasicFlow?

- **BasicFlow is a lightweight stabilization pipeline we developed**, combining ideas from SteadyFlow and MeshFlow with modern deep optical flow.
- Uses **RAFT (Recurrent All-Pairs Field Transforms)** to obtain dense, accurate optical flow. RAFT performs iterative refinement over an all-pairs correlation volume, giving very reliable flow even in low-texture or complex regions.
- Instead of SteadyFlow's heavy discontinuity analysis, BasicFlow applies a **simple spatial gradient mask** to detect unreliable flow areas.
- Replaces SteadyFlow's ASAP motion completion with **iterative diffusion** (selective blurring) to smooth and fill discontinuities.
- Uses MeshFlow's **PAPS** (Predicted Adaptive Path Smoothing) to choose smoothing strength  $\lambda_t$  without iterative search.
- Produces the final stabilization by **smoothing per-pixel motion profiles**, similar in spirit to SteadyFlow but far more efficient.

# BasicFlow: Pipeline

- **Dense Optical Flow (RAFT)** Compute high-quality dense optical flow between consecutive frames using RAFT with padding + cropping.
- **Discontinuity Detection** Compute Sobel gradients of the flow. Mark pixels with large gradient magnitude as unreliable (spatial mask).
- **Motion Completion via Diffusion** Run several iterations of selective blurring. Only update pixels inside the discontinuity mask  $\rightarrow$  smooth, hole-free flow.
- **Pixel Profile Construction** Accumulate cleaned flows over time to build motion profiles  $C(t)$  for every pixel.
- **Homography-Based Weight Estimation** Compute homographies between frames. Derive smoothing weights  $\lambda_t$  from translation and affine components.
- **Pixel Profile Smoothing (Jacobi Iteration)** Iteratively smooth each pixel's temporal motion profile to obtain stabilized motion trajectories  $P(t)$ .
- **Frame Warping and Output** Compute warp fields from  $P(t) - C(t)$ , warp each frame, crop borders, and write the stabilized video.

# BasicFlow: Deviations from Literature

- **No temporal outlier detection** SteadyFlow uses spatial *and* temporal discontinuity checks; BasicFlow uses only a one-pass spatial gradient threshold.
- **No ASAP motion completion** SteadyFlow fills holes via a large sparse linear solve (ASAP warping); BasicFlow replaces this with simple **iterative diffusion** (selective blurring).
- **Lambda estimation from MeshFlow (PAPS)** SteadyFlow searches iteratively for the best  $\lambda_t$ ; BasicFlow directly predicts it using MeshFlow's regression model.
- **Dense deep flow from RAFT** Removes reliance on sparse feature tracking (MeshFlow) or classical flow (SteadyFlow).
- **Simplified, linear pipeline** No iterative refinement, no heavy optimization → significantly faster in practice.

# Performance Metrics

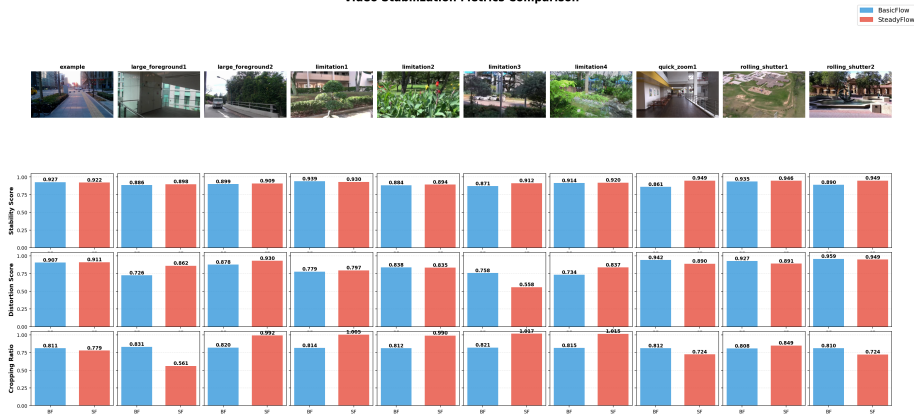
**Stability Score** Measures how well the output video suppresses unintended camera shake. Higher values indicate smoother global motion.

**Distortion Score** Evaluates geometric faithfulness of the stabilized video. Penalizes warping artifacts, local stretching, and shape deformation.

**Cropping Ratio** Represents how much of the original frame content is retained after stabilization. Higher ratios mean less cropping and better field-of-view preservation.

# Metrics Comparison

Video Stabilization Metrics Comparison



BasicFlow achieves similar or better performance across most videos, particularly in sequences involving large foreground motion, while maintaining comparable stability, lower distortion, and strong cropping ratios.

# Dominating Foreground

**Link:**

<https://youtu.be/1FxWuKNQEiM>



# Quick Zoom

**Link:**

<https://youtu.be/n95WHZevxD8>

# Rolling Shutter

**Link:**

<https://youtu.be/QkzGF9ZRE0I>

# All Comparisons

**Link:**

[https://www.youtube.com/playlist?list=PL2gpCaN00ukK0CCQrF3CXxn65Ktbnit\\_8](https://www.youtube.com/playlist?list=PL2gpCaN00ukK0CCQrF3CXxn65Ktbnit_8)

# Issues Addressed by BasicFlow

- **High computational cost in SteadyFlow** Replaces ASAP warping + iterative refinement with simple diffusion and predicted smoothing (PAPS), making the pipeline much faster.
- **Brittleness of feature tracking in MeshFlow** Uses dense RAFT optical flow instead of sparse features, avoiding failures in low-texture or uneven regions.
- **Latency from iterative parameter search** Removes SteadyFlow's iterative search for  $\lambda_t$ ; BasicFlow predicts it instantly through MeshFlow's PAPS model.

Thank You!  
Questions?