AInimotion

Layer-Separated Deformable Interpolation for Anime Video

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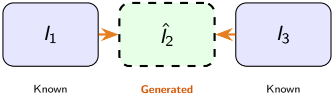
Video Frame Interpolation for Anime

Goal: Generate intermediate frames to increase frame rate (24fps $\rightarrow$ 60fps).



Why anime is uniquely challenging:

1. **Flat color regions** — no texture for optical flow
2. **Non-linear motion** — characters "pop" between poses
3. **Ink line preservation** — thin lines blur easily
4. **Scene cuts** — abrupt shot changes
5. **Layer separation** — backgrounds pan rigidly, characters move independently

Why Deep Learning?

Frames have **multi-scale spatial structure** (edges, textures, objects) and **temporal structure** (motion patterns across frames). Anime adds **layer structure**: rigid backgrounds vs. deformable characters. My model encodes these structural priors directly.

Prior Work & My Contribution

Prior Approaches:

Method	Idea	Gap
DAIN [7]	Depth-aware flow	Not anime-specific
AdaCoF [2]	Deform. kernels	Single motion path
AnimeInterp [1]	Segment match	Ext. segmentation
RIFE [3]	Lightweight flow	Blurs heavy motion
LDMVFI [8]	Latent diffusion	100$\times$ slower

Layer decomposition dates to Wang & Adelson (1994) [6], but **no prior VFI method** builds anime's layer structure into the architecture.

What makes AInimotion novel:

1. **Dual-path architecture** — dedicated BG (affine grid) + FG (AdaCoF kernels)
2. **Domain-informed** — encodes how anime is produced (cel layers)
3. **Learned compositor** — soft α mask, no external segmentation
4. **Edge-aware loss** — Sobel-weighted L1 protects ink lines
5. **Practical** — real-time inference ($\sim$50ms) vs. diffusion ($\sim$5–30s)

ATD-12K Dataset

Source: ATD-12K [1] (CVPR 2021)

- **12,000** frame triplets (I_1, I_2, I_3) from **30 films**
- Motion categories: small, medium, **large**
- Established anime VFI benchmark

Training setup:

- Random 384×384 crops
- Horizontal/vertical/temporal flips
- 100K samples per epoch

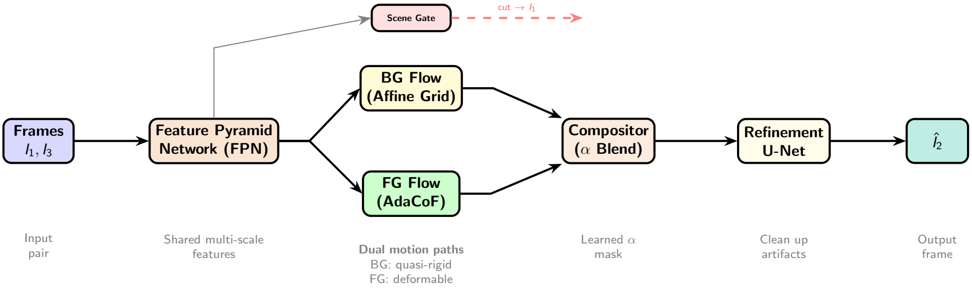
Why This Dataset?

- Purpose-built for anime VFI
- Publicly available
- Rich motion diversity
- Includes difficulty labels

Triplet Format

(I_1, I_2, I_3): I_2 is ground truth used as supervision during training.

Architecture Overview: LayeredInterpolator



Key Components & Loss Functions

Components:

- **FPN:** Shared encoder, 4 scales ($\frac{1}{2}$ to $\frac{1}{16}$) + **correlation volumes** (per-pixel dot-product similarity over a 9×9 search window between frames — tells the network "where did each pixel move?")
- **Scene Gate:** Detects hard cuts via correlation statistics, bypasses interpolation
- **Background:** 8×8 quasi-rigid affine grid for camera pans/zooms
- **Foreground (AdaCoF):** 9×9 deformable sampling kernels per pixel (81 weights + 162 offsets = 243 params/pixel)
- **Compositor:** Learned soft α mask + refinement U-Net

Generator Loss:

$$\mathcal{L}_G = \underbrace{1.5 \cdot \mathcal{L}_{L1}}_{\text{Reconstruction}} + \underbrace{0.1 \cdot \mathcal{L}_{\text{perc}}}_{\text{VGG19}} + \underbrace{1.0 \cdot \mathcal{L}_{\text{edge}}}_{\text{Ink Lines}} + \underbrace{0.005 \cdot \mathcal{L}_{\text{GAN}}}_{\text{Phase 2}}$$

- $\mathcal{L}_{L1}$: Pixel accuracy, drives PSNR
- $\mathcal{L}_{\text{perc}}$: VGG19 feature similarity, preserves style
- $\mathcal{L}_{\text{edge}}$: Sobel-weighted L1, 20× multiplier on edges
- $\mathcal{L}_{\text{GAN}}$: LSGAN patch discriminator with label smoothing (0.1), Phase 2 only

Two-Phase Training Strategy

Phase 1: Reconstruction (Ep 0–34)

- Generator only — no adversarial loss
- $\mathrm{lr}_G = 3 \times 10^{-4}$
- Loss: $\mathcal{L}_{L1} + \mathcal{L}_{\text{perc}} + \mathcal{L}_{\text{edge}}$
- **Goal:** PSNR $\geq$ 28 dB

$\Downarrow$ *D warmup (500 batches)*

Phase 2: GAN Fine-Tuning (Ep 35–49)

- Adversarial loss activated ($\lambda_{\text{GAN}} = 0.005$)
- $\mathrm{lr}_G = 5 \times 10^{-5}$ (reduced)
- D trains every other batch (1:2 ratio)
- **Goal:** perceptual sharpness

Why two phases?

1. Generator learns stable reconstructions *before* seeing adversarial gradients
2. GAN adds sharpness without destabilizing a converged generator

Key stabilization choices:

- **D warmup** — 500 batches before G sees GAN loss
- **Low GAN weight** (0.005) prevents mode collapse
- **Adaptive lr_D** — auto-adjusts based on d_{acc}
- **Label smoothing** (0.1) on discriminator

GAN Stabilization & Training Infrastructure

Discriminator Control:

- **D Warmup** (500 batches) — D learns before G sees adversarial loss
- **Patch Discriminator** — 70×70 patches, not full images
- **Label Smoothing** (0.1) — prevents overconfident D
- **D Update Ratio** (1:2) — D trains every other batch
- **Adaptive lr$_D$** — auto-adjusts based on d_{acc}

Evaluation Metrics:

- **PSNR** (dB): $-10 \log_{10}(\text{MSE})$. Higher $=$ better pixel accuracy. Log scale: $+3$ dB $\approx$ halving MSE.
- **SSIM**: Measures luminance, contrast, and structural similarity (0–1). Catches distortions PSNR misses.
- **Visual comparison**: Side-by-side with ground truth, especially on ink lines and motion.

Infrastructure

Mixed precision, grad_clip=1.0, OOM recovery, W&B logging. RTX 5090 (32 GB VRAM).

Design Evolution & Training Progress

Component	Initial	Final
Base Channels	32	96 (3×)
Kernel Size	7	9 (sweep winner)
GAN Training	From epoch 0	Two-phase (ep 35)
L1 Weight	1.0	1.5 (sweep-optimized)
GAN Weight	0.01	0.005 (gentler)
Edge Multiplier	10×	20× (sharper)
Disc. LR	10^{-4}	2×10^{-5}
D Update	1:1	1:2 (G trains more)
D Warmup	None	500 batches

Lesson: GAN training is highly sensitive in anime VFI. The discriminator easily dominates.

Evaluation Baselines (ATD-12K):

Method	PSNR	SSIM
RIFE	∼25–27 dB	∼0.85
AnimeInterp	∼27–29 dB	∼0.88
AInimotion (target)	**≥28 dB**	**≥0.90**

Sweep Results (13 experiments):

- Best: **21.80 dB** (K=9, crop 384, perc=0.1)
- Crop 384 alone: +0.74 dB over 256
- Gradients stable ($\sim$ 0.2–0.5)

Targets

Phase 1: PSNR $\geq$ 28 dB by epoch 34
Phase 2: + perceptual sharpness via GAN

Summary & Next Steps

What I built:

- **LayeredInterpolator** — novel dual-path architecture separating BG/FG motion
- **Edge-aware losses** for ink line preservation
- **Two-phase training** with D warmup for stable GAN integration
- **Robust infrastructure** — OOM recovery, adaptive GAN balancing, mixed precision, W&B logging

Next steps:

- Complete full 50-epoch training run
- Evaluate Phase 2 GAN fine-tuning
- Qualitative evaluation on test set
- Compare with RIFE, AnimeInterp baselines

Project Repository

`github.com/TWhit229/AInimotion`

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