SVMV: SPATIOTEMPORAL VARIANCE-SUPERVISED MOTION VOLUME FOR VIDEO FRAME INTERPOLATION

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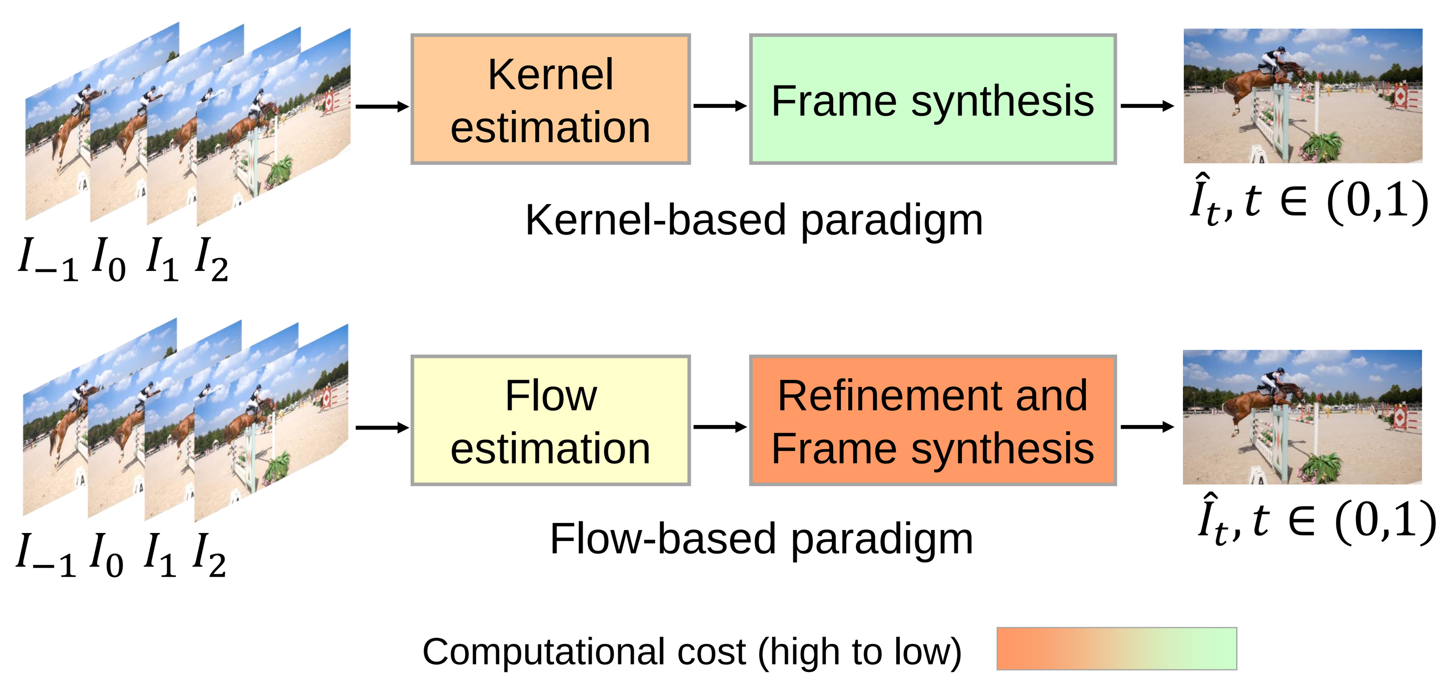
Background

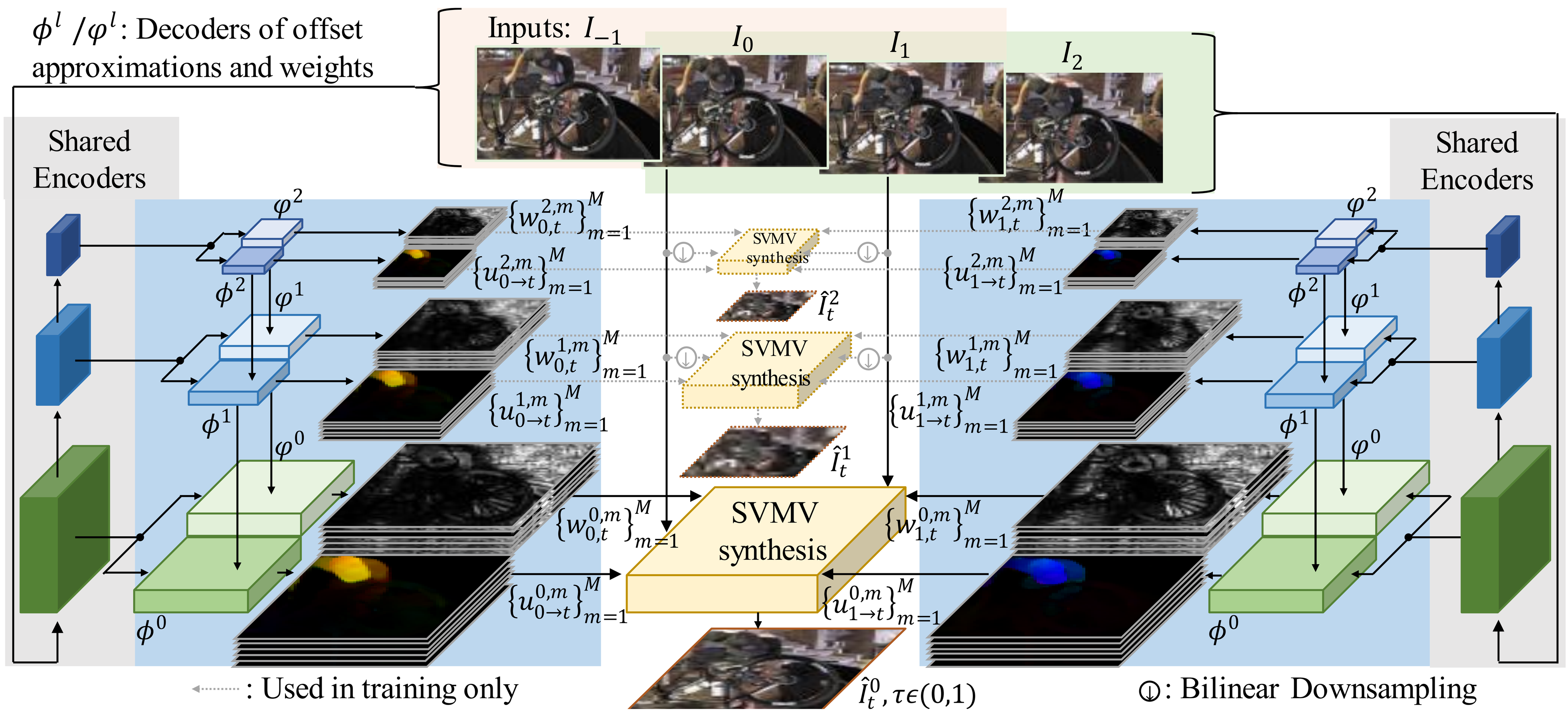
Video frame interpolation increases the frame rate of videos, and is required in various scenarios. Existing video frame interpolation methods utilizing deep learning consist of two paradigms:



- Kernel-based paradigm
  - Kernel estimation networks often have heavy structures
  - Kernel estimates may be deficient to handle large motion
- Flow-based paradigm
  - Learning accurate flow estimation is nontrivial
  - Utilizing refinement modules is both computationally expensive and vulnerable to error propagation

Motion Volume Construction and Synthesis

The motion volumes are constructed via a lightweight pyramidal network.



SVMV synthesis generates intermediate frame via ensembles of M offset approximations per pixel and corresponding weights.

$$\hat{I}_t[p_t] = \frac{\sum_{i=0}^{1} \sum_{m=1}^{M} \sum_{\forall q_i \in I_i} K_{i,t}^m[q_i] I_i[q_i]}{\sum_{i=0}^{1} \sum_{m=1}^{M} \sum_{\forall q_i \in I_i} K_{i,t}^m[q_i]}$$

B: bilinear kernel

$$K_{i,t}^m[q_i] = \omega_{i,t}^m[q_i] B(q_i + u_{i\to t}^m[q_i] - p_t)$$

q_i, p_t: pixel coordinates

- Yield ensemble of offset approximations to conduct flexible sampling process
- Learn shared spatiotemporal representations to achieve network compactness

Spatiotemporal Variance-aware Supervision

The spatiotemporal variance-aware loss L_{BV} is a sum of L_{sv} and L_{tv}, and is utilized along with the typical frame reconstruction loss to conduct self-supervised and supervised joint training for SVMV.

- A spatial variance enhance loss

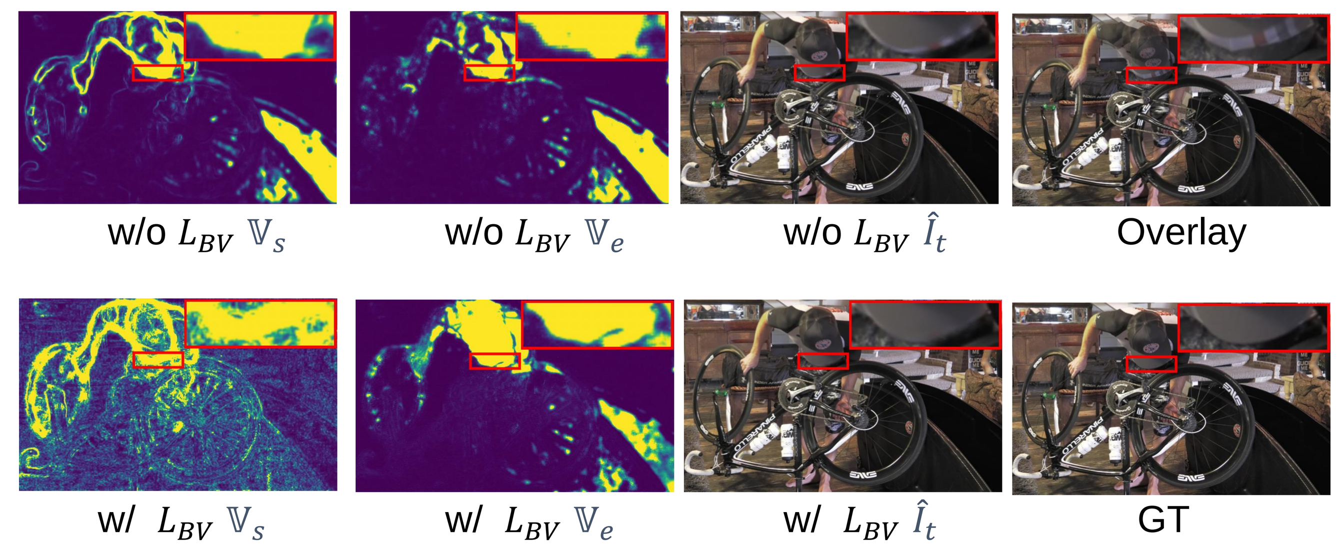
$$L_{sv}[q_i] = \mathbb{V}_s[u_{i\to t}[q_i]] / \mathbb{V}_e[u_{i\to t}[q_i]]$$

- A temporal variance enhance loss

$$L_{tv}[q_i] = \min\{L_{PE}(I_i[q_i], I_j[q_i + u_{i\to j}^m[q_i]]),\ L_{PE}(I_i[q_i], I_t[q_i + u_{i\to t}^m[q_i]])\}$$

L_{PE}: photometric reprojection loss

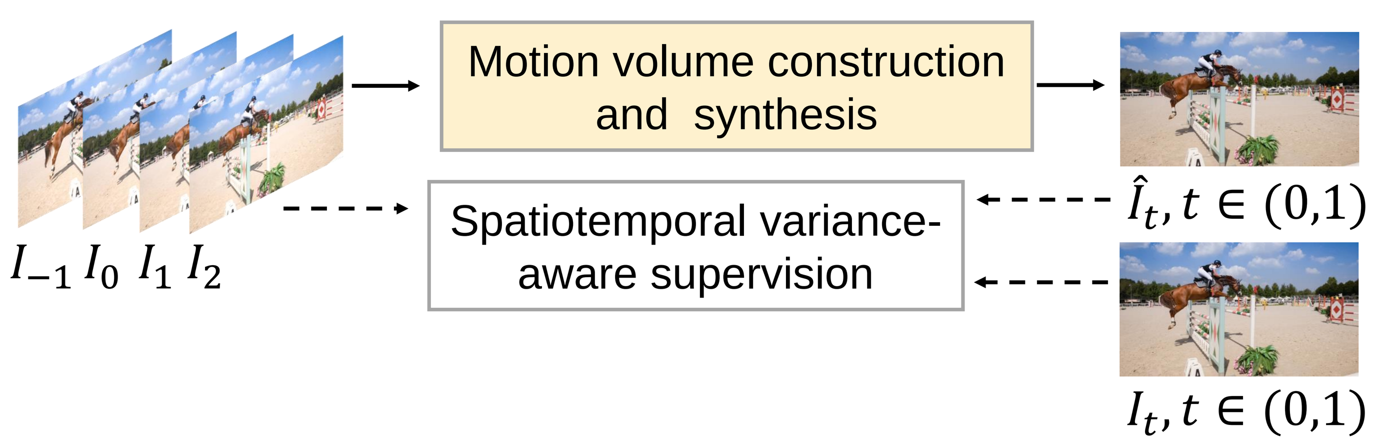
$\mathbb{V}_s, \mathbb{V}_e$: local spatial variance, per-pixel ensemble variance



- Exploit diverse offset approximations per pixel to refine the sampling process
- Avoid heavy refinement modules

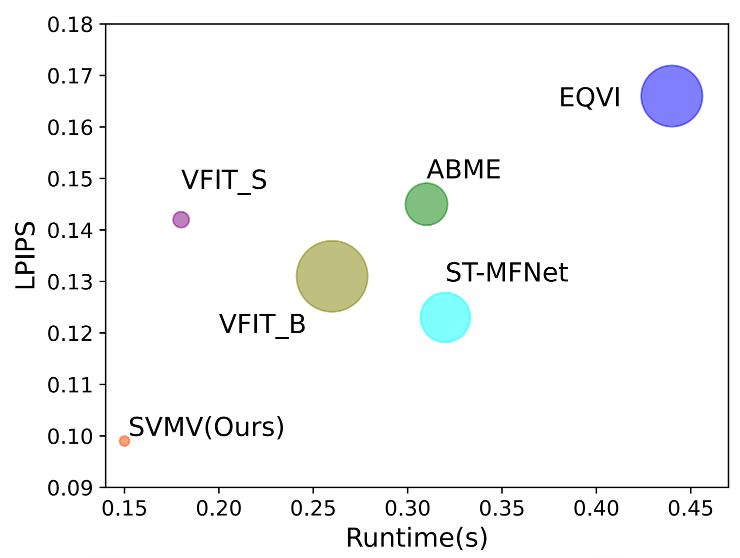
SVMV Overview

We propose SVMV framework, based on ensembles of offset approximations supervised by introducing a variance-aware loss, that assembles estimations and refinements.

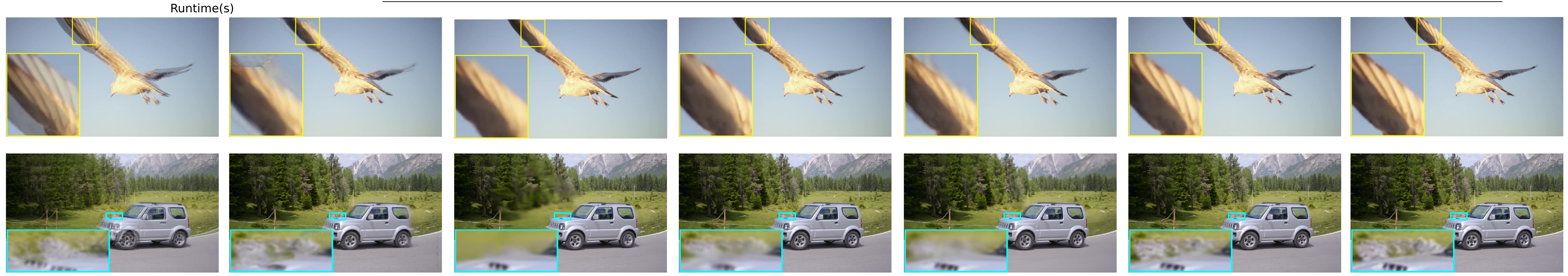


- SVMV method components
  - Motion volume construction and synthesis
  - Spatiotemporal variance-aware supervision
- SVMV method performance
  - Favorable interpolation results
  - More compact network
  - Less runtime

Comparisons on the SNU-FILM and DAVIS datasets against SOTA methods



Methods	FILM *(Medium)* PSNR↑/ SSIM↑ /LPIPS↓	FILM *(Hard)* PSNR↑ /SSIM↑ /LPIPS↓	FILM *(Extreme)* PSNR↑ /SSIM↑ /LPIPS↓	DAVIS PSNR↑ /SSIM↑ /LPIPS↓	Runtime(s)↓	Params(M)↓
EQVI	35.48 / 0.9667 / 0.050	30.65 / 0.9143 / 0.108	25.64 / 0.7968 / 0.197	27.64 / 0.8317 / 0.166	0.44	25.4
ABME	35.77 / 0.9650 / 0.037	30.58 / 0.9001 / 0.066	25.11 / 0.7809 / 0.131	26.98 / 0.8052 / 0.145	0.31	18.1
ST-MFNet	37.11 / 0.9733 / 0.036	31.70 / 0.9213 / 0.073	**25.81** / 0.8019 / 0.148	**28.36** / **0.8438** / 0.123	0.32	21.0
VFIT_B	36.49 / 0.9688 / 0.036	31.04 / 0.9086 / 0.076	25.49 / 0.7904 / 0.163	28.05 / 0.8280 / 0.131	0.26	29.0
VFIT_S	36.49 / 0.9693 / 0.036	31.06 / 0.9090 / 0.081	25.43 / 0.7879 / 0.174	27.90 / 0.8242 / 0.142	0.18	7.5
SVMV(Ours)	**37.14 / 0.9738 / 0.027**	**31.76** / **0.9244** / **0.059**	25.76 / **0.8036** / **0.126**	28.17 / 0.8411 / **0.099**	**0.15**	**4.8**



Overlay | EQVI (Liu, 2020) | ABME (Park, 2021) | ST-MFNet (Danier, 2022) | VFIT_B (Shi, 2022) | SVMV (Ours) | GT