
Digital Image Processing

Final Project Proposal

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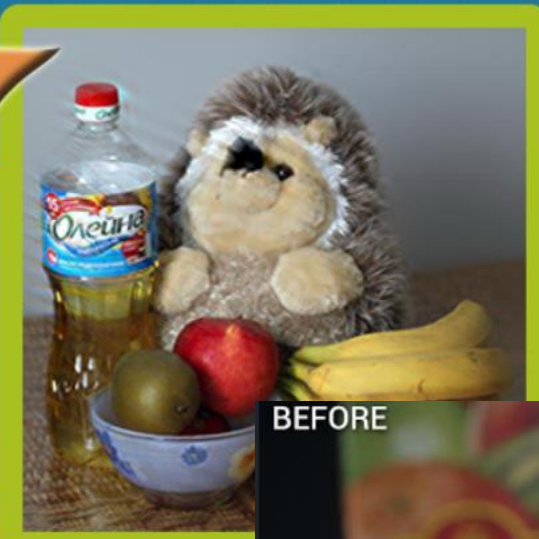
Group No. 19

Preface





Detected
Blur Path



DeblurGAN-v2 Paper



Introduction



Image Deblurring



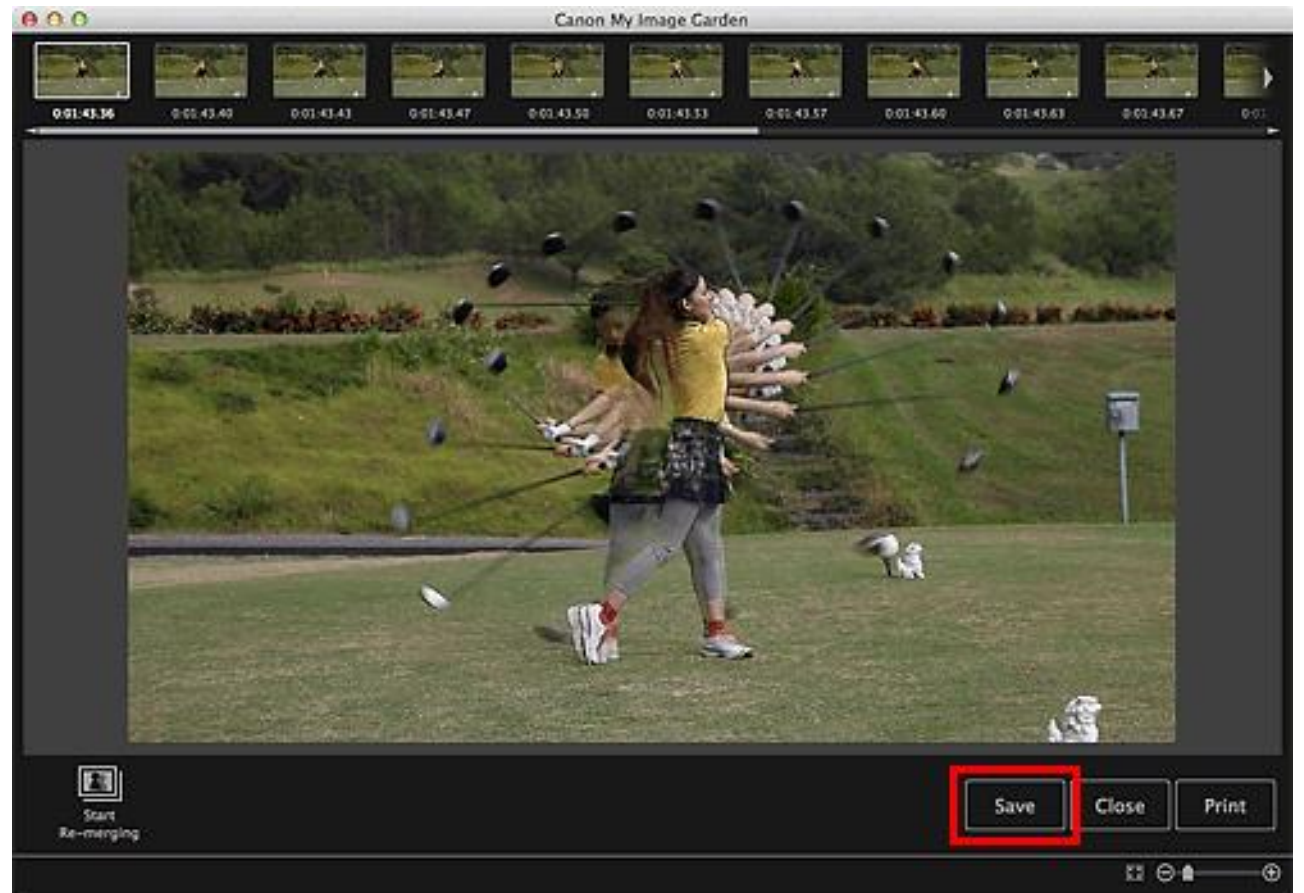
- Progress of GANs

$$I_B = k(M) * I_S + N,$$

- **The project is focused in three main parts :**
 1. Generate blurred images
 2. A method to deblur
 3. A novel method to quantify how good is a deblurred algorithm

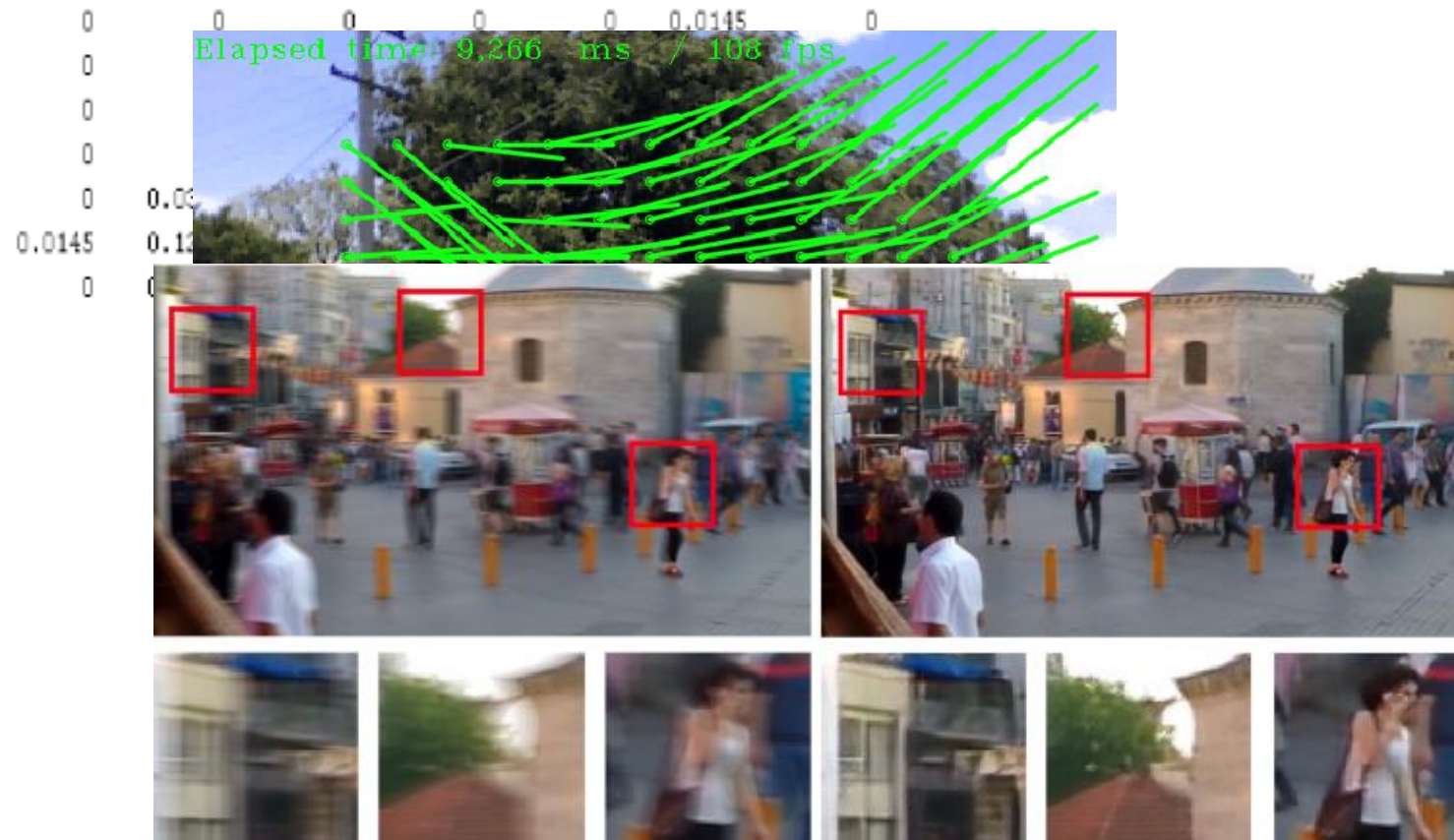
Blurred Image Generation

- Difficult to Dataset
- Take from video
- Convolving sharp images
- A novel method



Deblurring Methods

- Estimate the blur kernel
- Obtain the motion flow estimation
- Perform blind kernel-free image deblurring



Deblurring Algorithm Performance

- Run an object detection benchmark on yolo

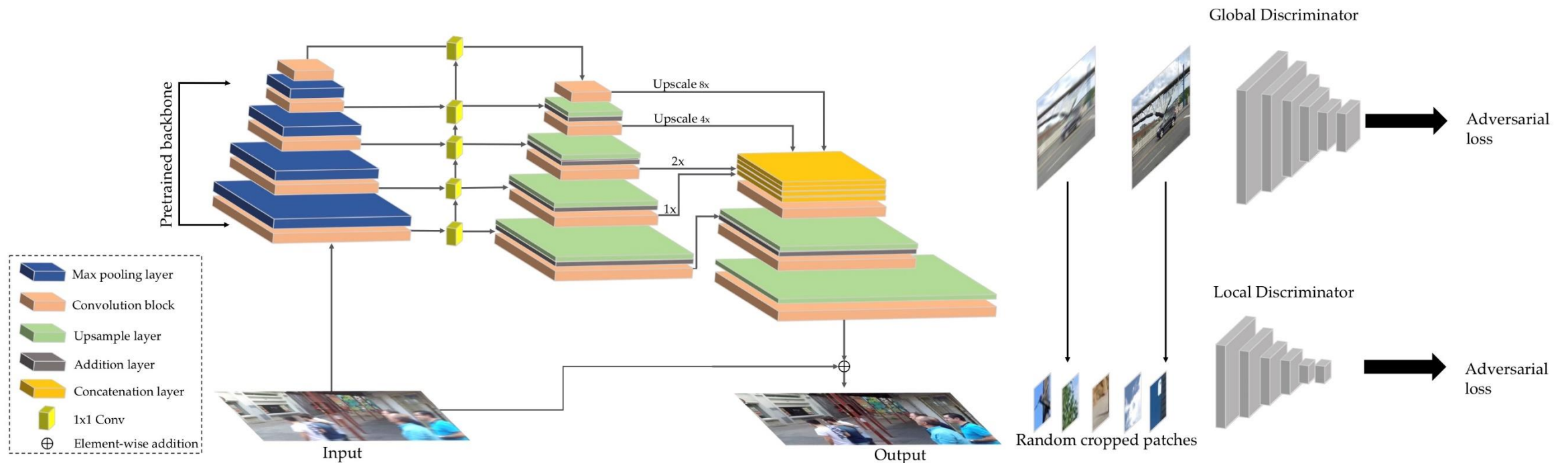


Architecture



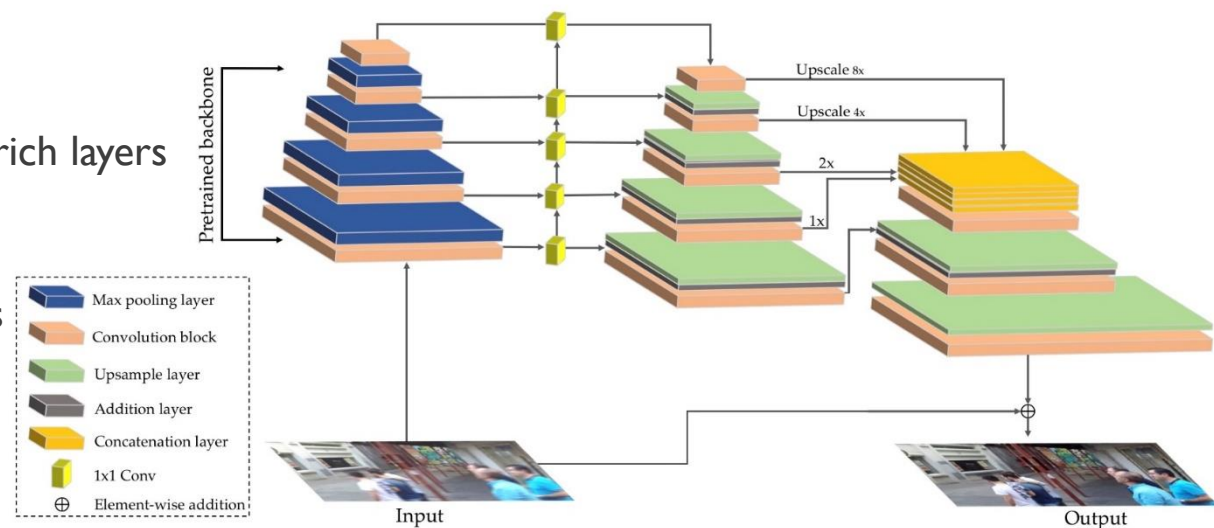
Feature Pyramid Deblurring

“A lighter-weight alternative to incorporate multi-scale features”
-Kupyn et al.



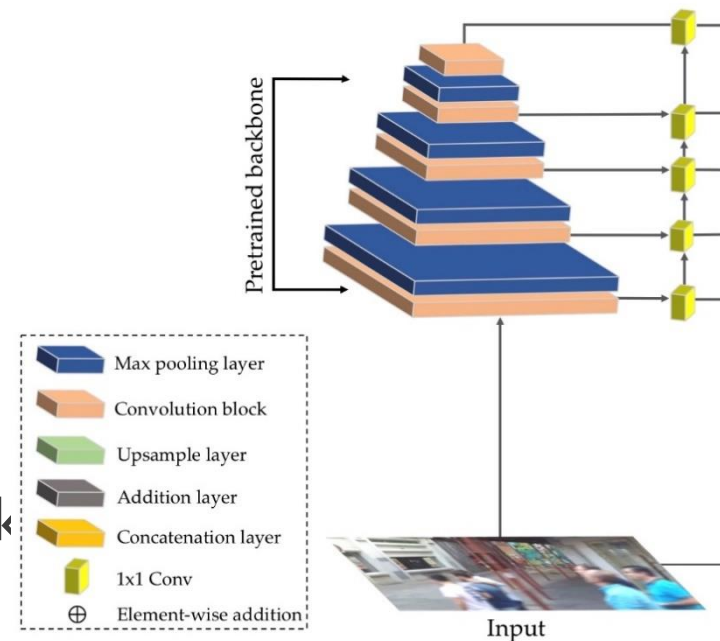
Feature Pyramid Deblurring

- Bottom-up pathway
 - Convolutional network for feature extraction
 - Down sampling of special resolution
 - Semantic context information is extracted and compressed
- Top-down pathway
 - Reconstruction of higher special resolution from semantic rich layers
- Lateral Connections
 - Supplement high-resolution details and help localize objects



Backbones

- Inception-ResNet-v2
 - Pursues strong deburring performance
- MobileNet-v2
 - For mobile on device enhancement
- MobileNet-DSC
 - Replaces all normal convolution in the full network
 - Extremely Light-weight
 - Efficient Deburring



Generative adversarial networks

- Two player minimax game Discriminator and Generator

- Goal is to capture the real data distribution

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

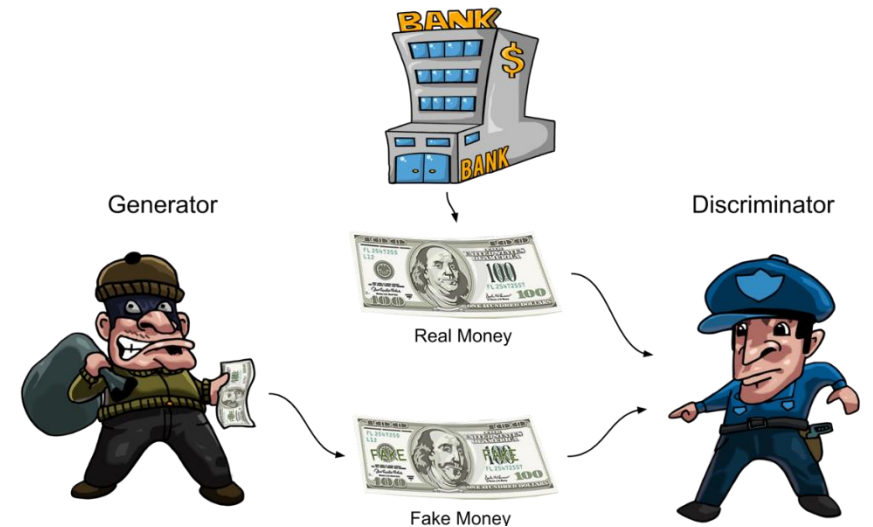
- Least Square GANs Discriminator

- Loss function that provides smoother and non-saturation gradient

$$\min_D V(D) = \frac{1}{2} \mathbb{E}_{x \sim p_{data}(x)} [(D(x) - 1)^2] + \frac{1}{2} \mathbb{E}_{z \sim p_z(z)} [D(G(z))^2] \quad \min_G V(G) = \frac{1}{2} \mathbb{E}_{z \sim p_z(z)} [(D(G(z)) - 1)^2]$$

- Relativistic GAN

- Estimates probability that given real data is more realistic than random fake sampled data



Double-Scale RaGAN-LS Discriminator

- Double Scale Discriminators to handle larger and more heterogeneous blurs

- Local branch

- Operates on patch levels
- Produces sharper results

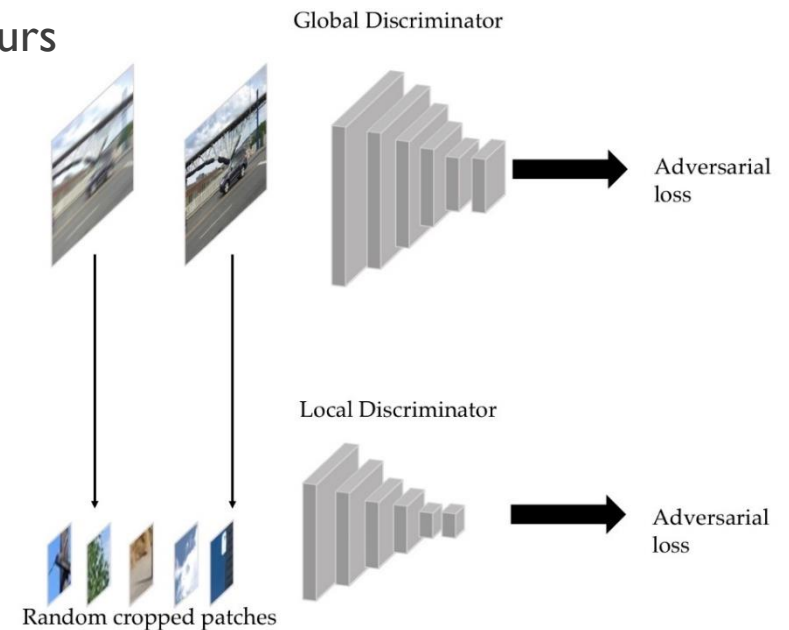
- Global branch

- Feed on full input image
- Better performance for highly non-uniform blurs

- Losses

$$L_D^{RaLSGAN} = \mathbb{E}_{x \sim p_{data}(x)} [(D(x) - \mathbb{E}_{z \sim p_z(z)} D(G(z)) - 1)^2] \\ + \mathbb{E}_{z \sim p_z(z)} [(D(G(z)) - \mathbb{E}_{x \sim p_{data}(x)} D(x) + 1)^2]$$

$$L_G = 0.5 * L_p + 0.006 * L_X + 0.01 * L_{adv}$$



Training Datasets

- GoPro:
 - GoPro Hero 4 camera
 - 240 fps video sequences
- DVD:
 - Multiple Devices
 - 71-real world videos sequences at 240 fps
- NFS:
 - iPhone 6 and iPad Pro
 - 75 videos with high frame rate
 - Youtube Videos

Experimental Evaluation



Quantitative Evaluation

- Evaluation metrics: PSNR and SSIM, inference efficiency

$$SSIM(x, y) = \frac{(2\mu_x \mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

$$MSE = \frac{1}{m n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - K(i, j)]^2$$

$$\begin{aligned} PSNR &= 10 \cdot \log_{10} \left(\frac{MAX_I^2}{MSE} \right) \\ &= 20 \cdot \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

Quantitative Evaluation

- Second best in some tests, but fastest by far; several order of magnitudes

Table 1: Performance and efficiency comparison on the GoPro test dataset, All models were tested on the *linear* image subset.

	Sun <i>et al.</i> [43]	Xu <i>et al.</i> [51]	DeepDeblur [33]	SRN [45]	DeblurGAN [21]	Inception-ResNet-v2	MobileNet	MobileNet-DSC
PSNR	24.64	25.10	29.23	30.10	28.70	29.55	28.17	28.03
SSIM	0.842	0.890	0.916	0.932	0.927	0.934	0.925	0.922
Time	20 min	13.41s	4.33s	1.6s	0.85s	0.35s	0.06s	0.04s
FLOPS	N/A	N/A	1760.04G	1434.82G	678.29G	411.34G	43.75G	14.83G

Table 2: PSNR and SSIM comparison on the Kohler dataset.

Method	Sun [43]	DeepDeblur [33]	SRN [45]	DeblurGAN [21]	Inception-ResNet-v2	MobileNet	MobileNet-DSC
PSNR	25.22	26.48	26.75	26.10	26.72	26.36	26.35
SSIM	0.773	0.807	0.837	0.816	0.836	0.820	0.819

Table 3: Results on DVD dataset

	PSNR	SSIM	Inference Time	Resolution
WFA	28.35	N/A	N/A	N/A
DVD (single)	28.37	0.913	1.0s	960 x 540
DeblurGAN-v2 (MobileNet)	28.54	0.929	0.06s	1280 x 720

Visual Comparison

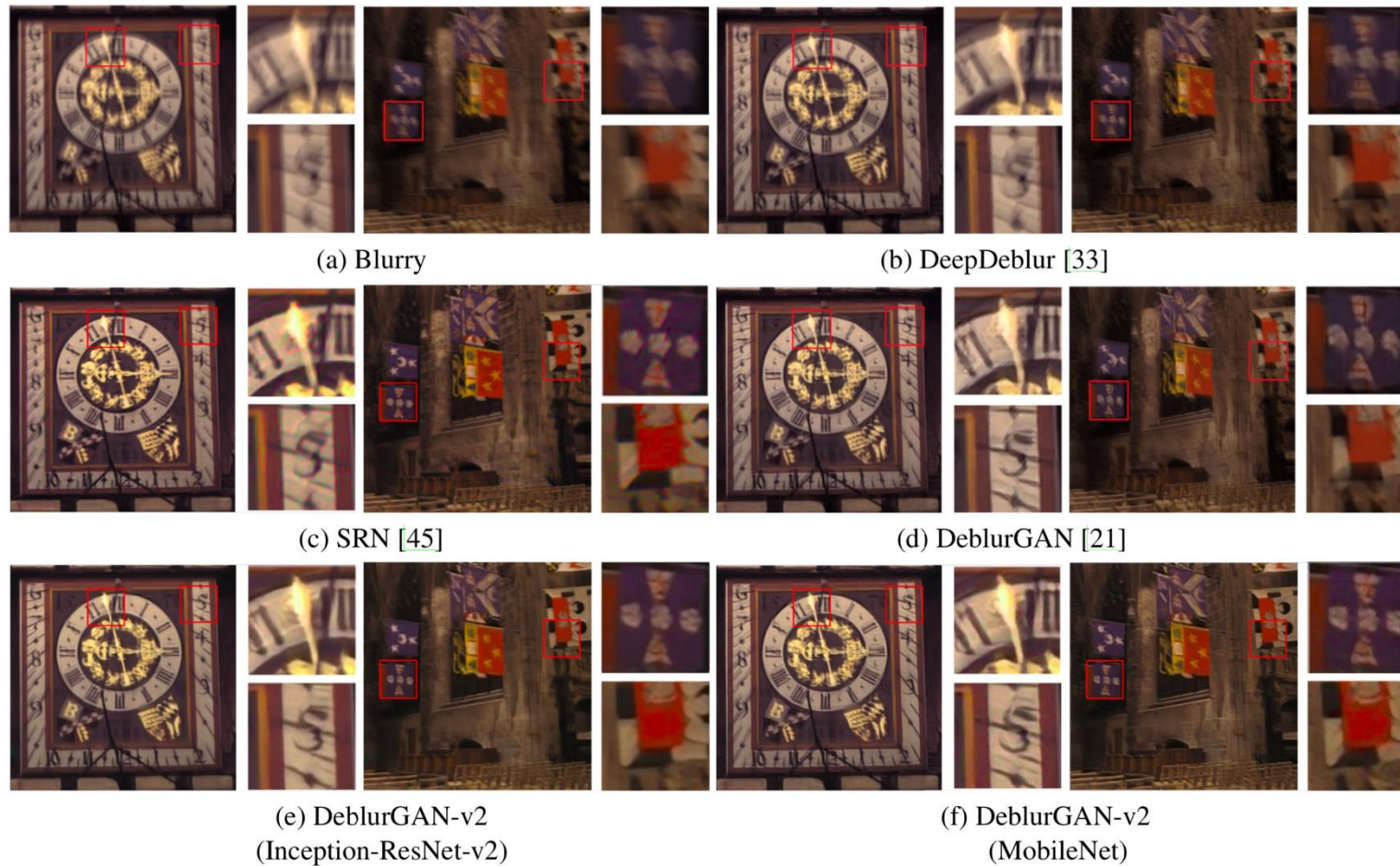


Figure 7: Visual comparison on the Kohler dataset.

Ablation Study

- DeblurGAN (ResNet G, local-scale patch D, WGAN-GP + perceptual loss)

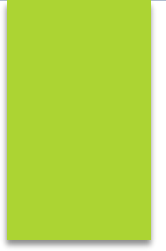
modifications study:

- Generator: adding FPN
- Discriminator: adding global-scale
- Loss: replacing WGAN-GP with RaGAN-LS and adding MSE term

Table 5: Ablation Study on the GoPro dataset, based on DeblurGAN-v2 (Inception-ResNet-v2).

	PSNR	SSIM
DeblurGAN (starting point)	28.70	0.927
+ FPN	29.26	0.931
+ FPN + Global D	29.29	0.932
+ FPN + Global D + RaGAN-LS	29.37	0.933
DeblurGAN-v2 (FPN + Global D + RaGAN-LS + MSE Loss)	29.55	0.934
Removing perceptual loss (replace 0.5 with 0 in L_G)	28.81	0.924

Final Project Proposal



DeblurGAN-v2(deo)

- Currently allows single image deblurring
- Make pipeline for video (blurring and) deblurring
- Evaluating deblurred video image quality to original



DeblurGAN-v2(deo)

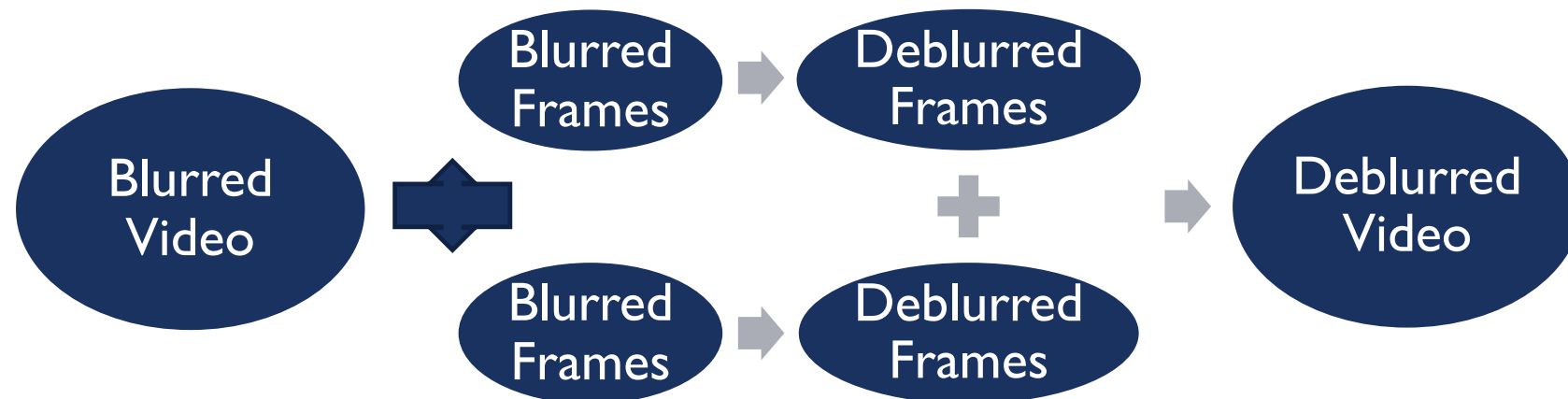
- Alternative pipeline for naturally blurry video:
 - Low framerate
 - Lack of proper illumination
 - Camera movement



DeblurGAN-v2(deo)

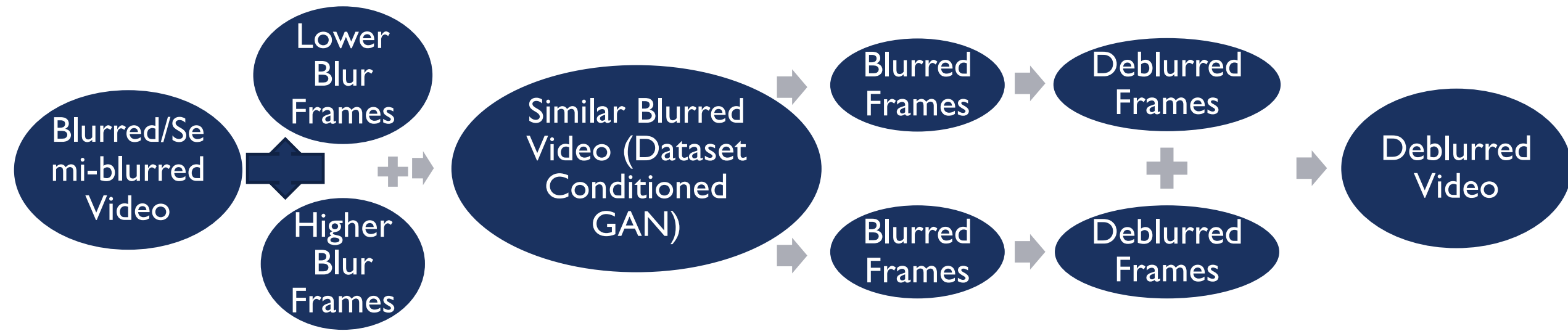
- Other possible lines of improvement come from HPC (High-Performance Computing) side:

- Parallel processing of frames for obtaining close to real-time deblurring



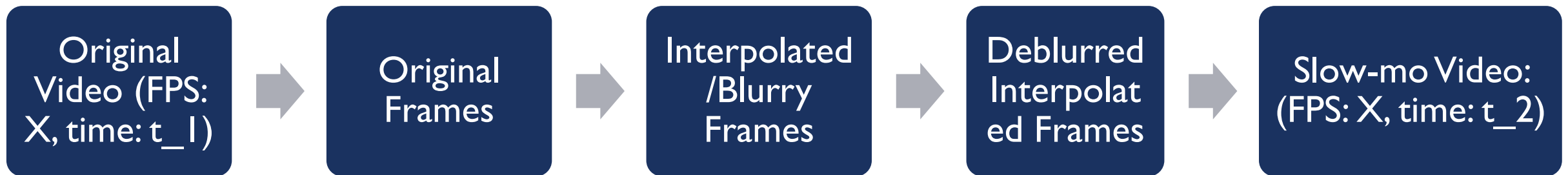
DeblurGAN-v2(deo)

- Even more ambitious (and advanced pipeline): fine-tuning network on the go with input video blur/deblurred image-pairs with high-learning rate/loss penalization for conditioning to new dataset



SupraFPS

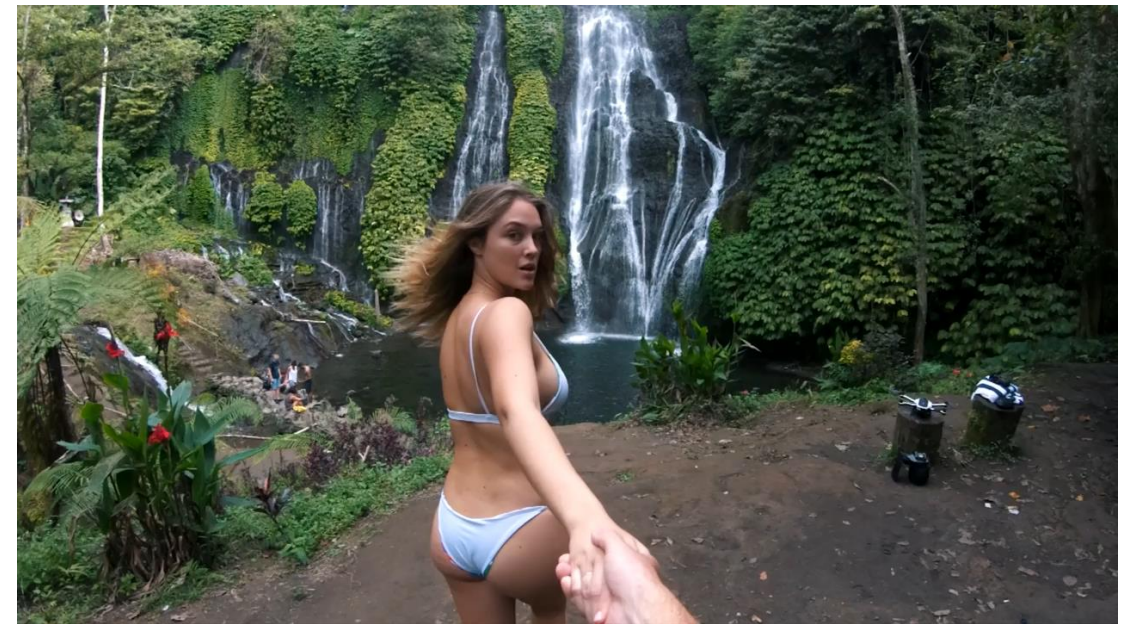
- Super Resolution for FPS of videos: 30 FPS to 120 FPS (slow-motion)
- Naive/simple approach: linear/weighted interpolation of video frames



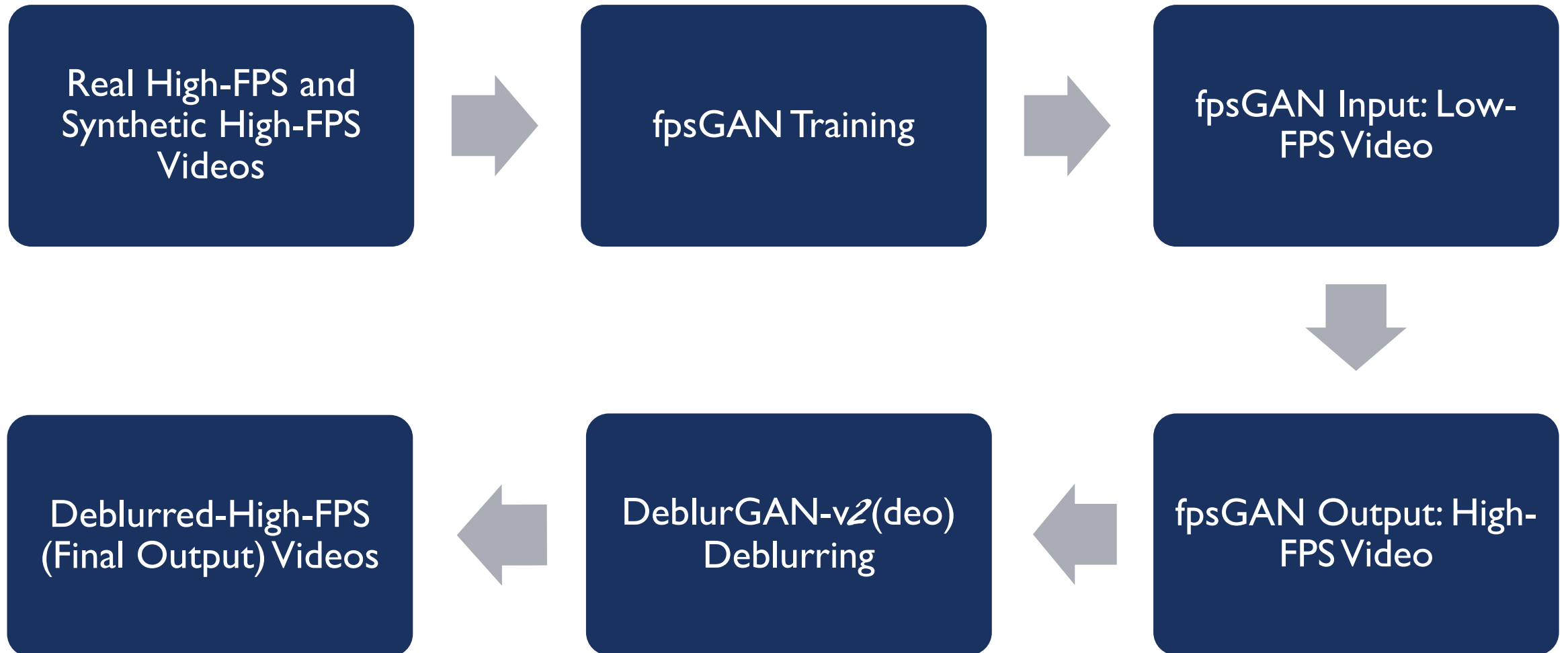
*X: FPS of original video, t_1 : duration in time (s) of original video, t_2 ($t_2 > t_1$): duration in time (s) of new video

fpsGAN

- More-advanced approaches: use kernel for motion estimation to get interpolated frames, CNNs
- GAN-boosted approach: fpsGAN
 - Real high FPS video, down-sample to low FPS pairs and use network to generate/learn difference between the real high FPS videos and the ones generated from our previous approaches
 - Use the results of fpsGAN (which are probably not that accurate) through deblurGAN-v2(deo) and compare to results through only fpsGAN



SupraFPS Advanced Pipeline



References

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