











Denys Rozumnyi^{1,4}, Martin R. Oswald¹, Vittorio Ferrari², Jiří Matas⁴, Marc Pollefeys^{1,3}

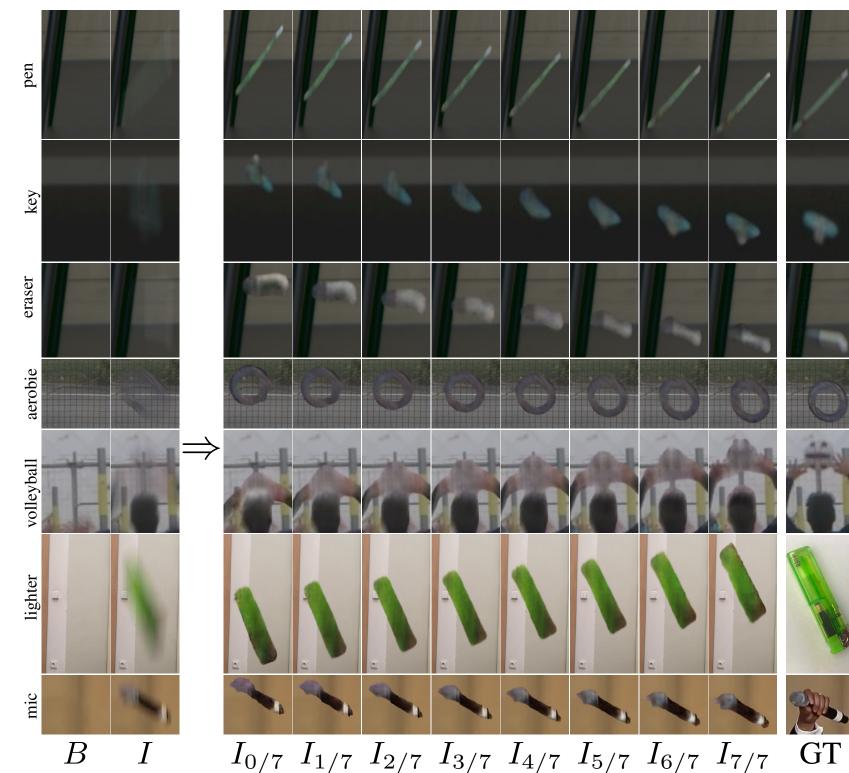




¹Department of Computer Science, ETH Zurich ³Microsoft Mixed Reality and Al Zurich Lab ⁴Visual Recognition Group, Czech Technical University in Prague ²Google Research

Introduction:

- > **Setting**: Motion blur is exceptionally ambiguous for fast moving objects (FMOs) – objects that move over a distance larger than their size within the camera exposure time.
- > Input: image / with an object moving fast and thus appearing blurred, background *B* without the object.
- > Task: reconstruct sub-frames as if this was a short video captured by a high-speed camera (temporal super-resolution).



> Image formation model for an FMO with constant appearance F and shape *M* moving along trajectory *H* over background *B*:

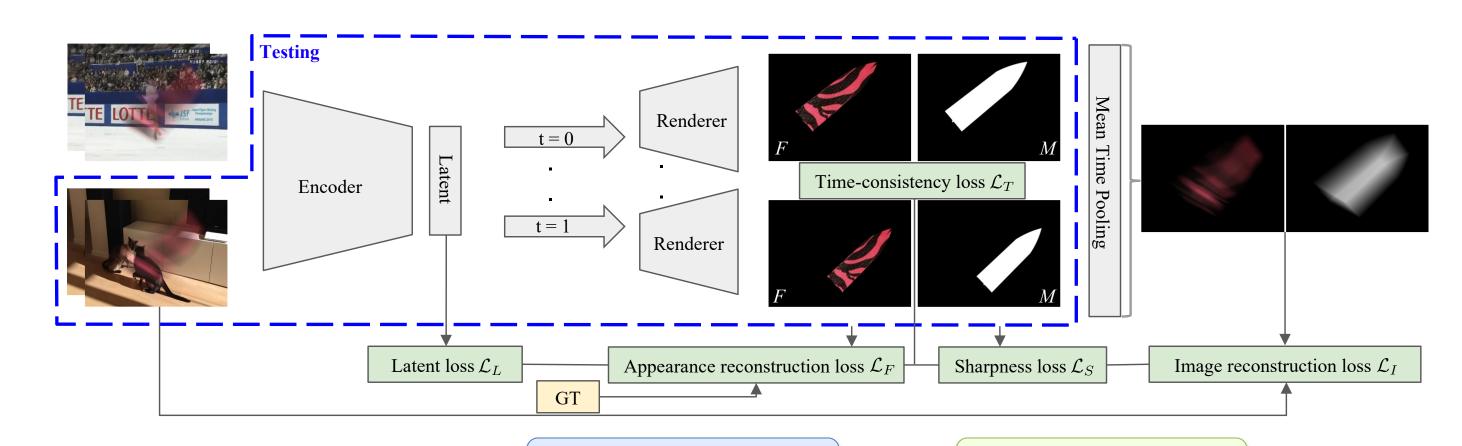
$$I = H * F + (1 - H * M) \cdot B$$

 \triangleright For time-varying F_i and M_i , TbD-3D defined a sub-frame formation model; cannot deal well will complex objects or complex motions:

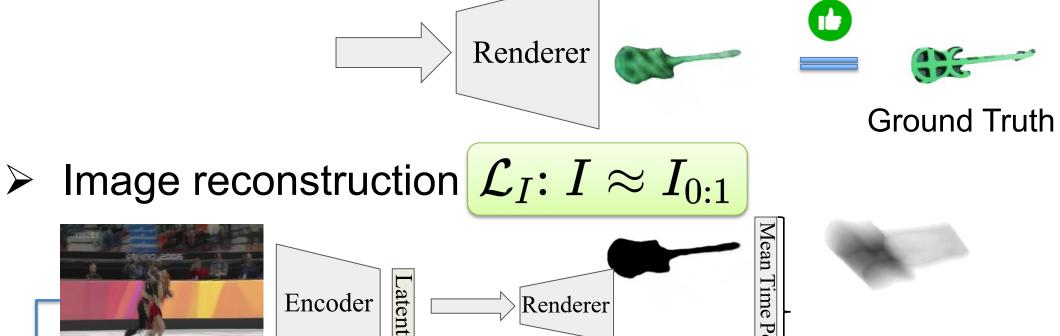
$$I = \sum_{i} H_i * F_i + \left(1 - \sum_{i} H_i * M_i\right) \cdot B$$

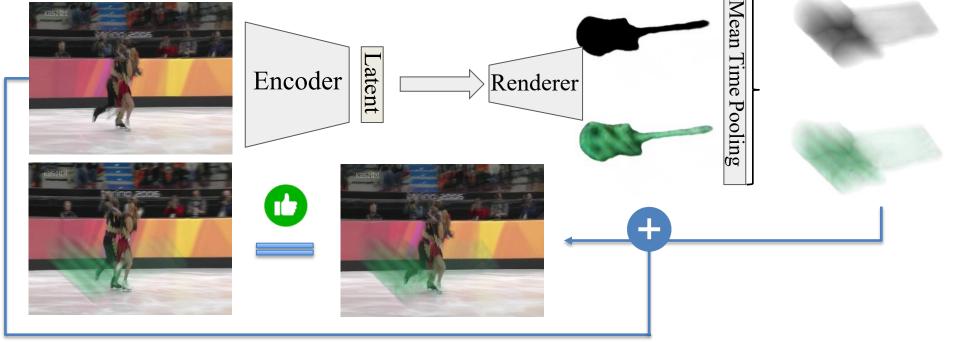
Method:

- > We propose a new generalized image formation model with FMOs, which generalizes all previous ones: $I_{t_0:t_1} = \int_{t}^{t_1} F_t M_t \,\mathrm{d}t + \left(1 - \int_{t}^{t_1} M_t \,\mathrm{d}t
 ight) B$
- \triangleright We treat F_t and M_t as a rendering network.

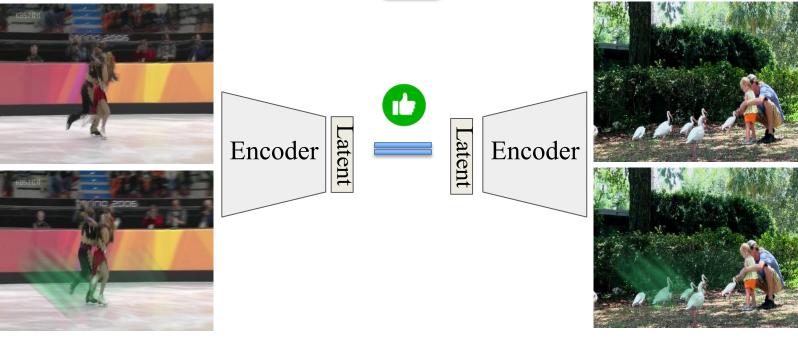


- ➤ We have 5 loss terms: a supervised loss and 4 self-supervised ones.
- \succ Sub-frame appearance reconstruction $\mathcal{L}_F: (F_t, M_t) pprox (ilde{F}_t, ilde{M}_t)$





 \succ Latent learning loss \mathcal{L}_L



Time-consistency $\mathcal{L}_T \!\!: (F_t, M_t) pprox (F_{t+\mathrm{d}t}, M_{t+\mathrm{d}t})$

Sharpness

$$oxedsymbol{\mathcal{L}_S} = \operatorname{entropy}(M_t)$$

Experiments:

We evaluate on TbD, TbD-3D, and Falling Objects datasets.

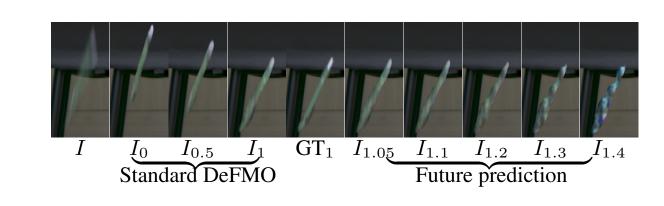
•	Typical Object	Score	Inputs			Compared Mo	Proposed	Traj. Oracle		
	Typical Object		B	I	Jin et al.	DeblurGAN-v2	TbD	TbD-3D	DeFMO	TbD-3D-Or.
T-11:52		TIoU↑	N/A	N/A	N/A	N/A	0.539	0.539	0.684	1.000
		PSNR↑	19.71	23.76	23.54	23.36	20.53	23.42	26.83	23.38
		SSIM↑	0.456	0.594	0.575	0.588	0.591	0.671	0.753	0.692
4 4		TIoU↑	N/A	N/A	N/A	N/A	0.598	0.598	0.879	1.000
		PSNR↑	19.81	24.80	24.52	23.58	18.84	23.13	26.23	24.84
		SSIM↑	0.426	0.640	0.590	0.603	0.504	0.651	0.699	0.705
Ę		TIoU↑	N/A	N/A	N/A	N/A	0.542	0.542	0.550	1.000
		PSNR↑	21.48	25.06	24.90	24.27	23.22	25.21	25.57	26.36
		SSIM↑	0.466	0.568	0.530	0.537	0.605	0.674	0.602	0.712
_	Runtime (on 24)	0×320)	N/A	N/A	2 fps	10 fps	0.01 fps	0.001 fps	20 fps	0.001 fps

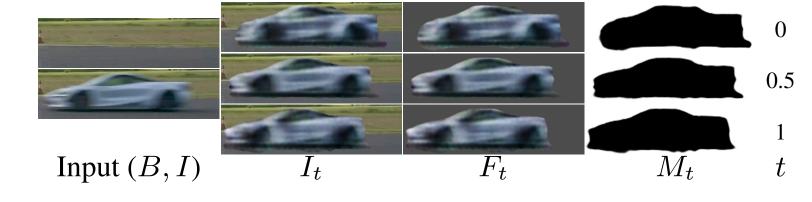
We beat everything.

Ablation study shows that each loss brings improvement.

Appear. rec.	Image rec.	Time-cons.	Latent learn.	Sharpness	Train	_Val	Test –	Falling (Objects
\mathcal{L}_F	\mathcal{L}_I	\mathcal{L}_T	\mathcal{L}_L	\mathcal{L}_S	PSNR↑	PSNR↑	PSNR↑	SSIM↑	TIoU
TbD)-3D				6.58	6.59	23.0	.695	.545
\checkmark	X	X	X	X	23.0	22.6	24.8	.691	.684
\checkmark	\checkmark	X	X	X	22.5	22.2	25.5	.705	.653
X	\checkmark	\checkmark	\checkmark	\checkmark	11.6	10.9	19.7	.459	.347
\checkmark	X	\checkmark	\checkmark	\checkmark	12.3	12.2	17.5	.362	.489
\checkmark	\checkmark	X	\checkmark	\checkmark	21.6	21.5	25.8	.743	.673
\checkmark	\checkmark	\checkmark	X	\checkmark	22.2	22.0	26.1	.739	.678
\checkmark	\checkmark	\checkmark	\checkmark	X	22.4	22.2	26.4	.750	.676
\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	22.5	22.4	26.4	.753	.703
	\mathcal{L}_F Appear.	$\begin{array}{ccc} \text{TbD-3D} & \text{Sphear} \\ \mathcal{L}_F & \mathcal{L}_I \\ \text{TbD-3D} & \checkmark & \checkmark \\ \checkmark & \checkmark & \checkmark \\ \hline & \checkmark & \checkmark \\ \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	TbD-3D $ \begin{array}{cccccccccccccccccccccccccccccccccc$	as a series of the series of	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

> The proposed model handles FMOs with complex shapes and significant appearance changes within one video frame.





Conclusion:

- We proposed a novel generative model for disentangling and deblurring of fast moving objects.
- Code is published on GitHub: https://github.com/rozumden/DeFMO
- Benchmark: https://github.com/rozumden/fmo-deblurring-benchmark

References:

[TbD] Kotera et al. Intra-frame Object Tracking by Deblatting, ICCV VOT 2019 [TbD-3D] Rozumnyi et al. Sub-frame Appearance and 6D Pose Estimation of Fast Moving Objects, CVPR 2020 [Falling Objects] Kotera et al. Restoration of Fast Moving Objects, TIP 2020