

DLSS 2.0 - IMAGE RECONSTRUCTION FOR REAL-TIME RENDERING WITH **DEEP LEARNING**

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ABOUT ME

7 years of real-time rendering research and development at NVIDIA Key contributors to several next-gen rendering technologies

• DLSS, real-time ray tracing and denoising, VR Rendering

Developed technologies/algorithms that shipped in many titles and game engines



NEXT GEN GAMES NEED SUPER RESOLUTION

Ray tracing, physics, AR/VR, and higher resolution displays drive up GPU computing needs exponentially Ray tracing alone can demand many times the computing power of traditional rendering techniques Super resolution technique become necessary

RTX GPUs have tensor cores to accelerate deep learning workloads











DLSS 1.0





INTRODUCING DLSS 2.0







Great Image Quality Details rival native resolution

4x Upscaling Ratio 540p to 1080p, 1080p to 4k

Generalized Model One model to rule them all!



1.5ms at 4K on 2080Ti Works on all RTX GPUs at all resolution

































1080p TAA

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540p TAA





540p - 89fps



1080p - 48fps



540p to 1080p w/ DLSS2.0 - 86fps



1080p - 48fps



540p to 1080p w/ DLSS2.0 - 86fps



32spp Reference 1080p



540p to 1080p w/ DLSS2.0 - 86fps



32spp Reference 1080p



540p DLSS2.0

32spp Reference 1080p TAA

540p TAA



DLSS 2.0 - ACCELERATED RENDERING







DLSS 2.0 PERFORMANCE BOOSTS

Performance Mode - 1080p to 4K





DLSS is impressive to the point where I believe you'd be nuts not to use it."

"The upscaling power of this new Al driven algorithm is extremely impressive... it's basically a free performance button."

- Digital Foundry

- Hardware Unboxed

SHIPPING IN THE FOLLOWING TITLES







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CHALLENGES IN IMAGE SUPER-RES FOR REAL-TIME RENDERING


- Ground Truth Function
- Discrete Samples
- **Reconstructed Function**





Double the sampling rate



- Ground Truth Function
- Discrete Samples
- **Reconstructed Function**





















DLSS PROBLEM STATEMENT





Low resolution sampling rate



High resolution reconstruction





DLSS PROBLEM STATEMENT



Cost of Rendering

≥ nvidia.

SINGLE IMAGE SUPER-RES Previous work

Reconstruct high resolution image by interpolating the low-resolution pixels

Common choices are bilinear, bicubic, lanczos

Contrast aware sharpening

deep neural networks can hallucinate new pixels conditioned on existing pixels based on priors or training data



bicubic (21.59dB/0.6423)



SRResNet (23.53dB/0.7832)

SRGAN (21.15dB/0.6868 original





[Ledig et al. 2017]



SINGLE IMAGE SUPER-RES

Resulted images lack details compared to native high-resolution images

Images may be inconsistent with native rendering because of hallucination, and temporally unstable



linear interpolation



High res samples



SINGLE IMAGE SUPER-RES

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DL Upscaled 720p to 1080p



Native Rendering 1080p

1080p with TAA



540p to 1080p DLSS2.0



540p Bicubic Upsampled to 1080p



540p to 1080p with ESRGAN

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MULTI-FRAME SUPER-RES Previous work

Less ill-posed than single image super-res, restore true optical details better

Designed for videos or burst mode photography, not leveraging rendering specific information

- Optical flow vs. geometric motion vector
- Pixels vs samples
- Using frames in the future

Bicubic

[Wronski et al. 2019]

Our result

HR frame [Sajjadi et al. 2018] 53

SPATIAL-TEMPORAL SUPER SAMPLING

Previous work

Temporal Antilasing (TAA)

[Yang09, Lottes11, Sousa11, Karis14, Salvi16]

Temporal Upsampling

Checkerboard Rendering (CBR)

[Yang09, Herzog10, Malan12, Valient14, Aalto16, Epic18]

[ElMansouri16, Carpentier17, Wilidal17]

References can be found in <A Survey of Temporal Antialiasing Techniques>, Yang et al.

SPATIAL-TEMPORAL SUPER SAMPLING

Reconstruct high resolution image using samples from across multiple frames Effective sampling rate drastically increased

Reconstructed image much closer to ground truth

Ground Truth Function

Prev. Function

Discrete Samples

Prev. Discrete Samples

Reconstructed Function

SPATIAL-TEMPORAL SUPER SAMPLING The devil's in the details

Samples from previous frames might no longer be correct due to content changes Using samples from previous frame naively might lead to artifacts like ghosting

SPATIAL-TEMPORAL UPSAMPLING History Rectification

Traditional spatial-temporal upsampling algorithms leverages heuristics to rectify invalid samples from previous frames However common rectification heuristics often trade off between different artifacts: Blurriness, temporal instability, even moire pattern vs. lagging and ghosting

[Yang et al. 2020]

NEIGHBORHOOD CLAMPING

Most commonly used sample rectification technique [Karis14], [Salvi16] Clamp previous frames samples to the min/max of the neighboring current frame samples Resulted in loss in details in the reconstructed image

Prev. Discrete Samples

Ghosting Happens without History Rectification

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NEIGHBORHOOD CLAMPING

Blurriness/Losing details

1spp Input

Reconstruction with clamping

Reconstruction without clamping [Yang et al. 2020]

NEIGHBORHOOD CLAMPING

Blurriness/Losing detail

When perform temporal upsampling, clamping introduces more loss in detail Since bounding boxes are calculated from a low-resolution image

Reconstruction with clamping, 1/4 res input Reconstruction w/o clamping, 1⁄4 res input

Reconstruction with clamping, 1/4 res input

Temporal Instability 1080p TAA with clamping

ARGO

Temporal Instability 540p to 1080p TAAU with Clamping

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NEIGHBORHOOD CLAMPING Temporal Instability and Moire

540p to 1080p TAAU w/o Clamping

ARGO

REAL-TIME SUPER-RES CHALLENGES

- Single frame approach
 - Blurry image quality
 - Inconsistent with native rendering
 - Temporally unstable
- Multi-frame approach
 - Heuristics to detect and rectifies changes across frames
 - Limitation in heuristics causing blurriness, temporal instability and ghosting

DLSS 2.0: DL BASED MULTI-FRAME RECONSTRUCTION

DLSS uses a neural network trained from tens of thousands of high-quality images Neural networks are much more powerful than handcrafted heuristics Much higher quality reconstructions using samples from multiple frames

Multi-frame samples and GT function

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Non-DL reconstruction

DLSS reconstruction

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1080p TAA

540p DLSS 2.0

1080p TAA

540p DLSS 2.0





