Event-driven Video Frame Synthesis
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captured data
intensity image + events

pre-processing
binning events to frames

DMR
differentiable model-based reconstruction

Residual "denoising" learning to remove DMR artifacts

global skip connection

cov + BN + ReLU
conv + ReLU
conv + ReLU

final output
synthesized video

What’s event camera?

Conventional camera

Event camera

Intensity values
Low speed: 30, 60 fps
Low dynamic range (60-90dB)
High power consumption
Low noise

Brightness changes (binary)
High speed: <1us latency
High dynamic range (120dB)
Low power consumption
Severe noise

Intensity + events: differentiable modeling

Objective and loss functions

Enhancement via residual learning

Results

Frame interpolation

Blurry image

Ours (DMR)

Ground truth

Ours (DMR) DnCNN FFTNet Ours (RD) Ground truth

EDI (CVPR’19) Ours (DMR)

Ours (RD)

CF (ACCV’18)

SepConv (CVPR’17)

Ours (DMR+RD)

Ours (RD)

PSNR: 23.33 SSIM: .771
PSNR: 25.12 SSIM: .831

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• Use CNN to learn the residual of DMR output w.r.t.
ground truth
• Designed to enhance DMR results
• Easy to train
• Model DMR artifacts as residual “noise”
• Actually beyond Gaussian denoising
• Single frame based
• Interface well with DMR

Motion deblur

Image+events

Ours (DMR) DnCNN FFTNet Ours (RD) Ground truth

EDI (CVPR’19) Ours (DMR)