Optimization Techniques of Deep Learning Models for Visual Quality Improvement

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Introduction

(a) Original

(b) Low-resolution

(c) Super-resolution

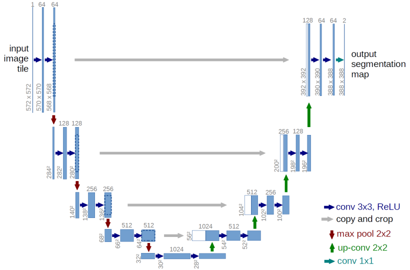
- Goal: Improve video restoration with deep learning models
- Challenge: Computational complexity of deep learning models
- Solution: Apply quantization techniques for faster inference and reduced memory usage

- Focus: Artefact removal and super-resolution tasks
- Method: Post-training quantization using TensorRT
- Impact: Enable practical deployment on resource-constrained devices

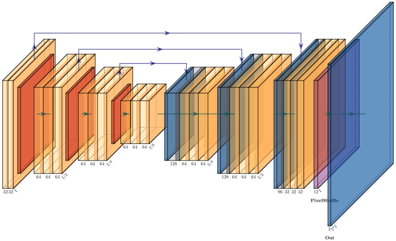
Quality Metrics for Video Restoration

- Traditional Metrics:
  - Evaluate image quality based on numerical comparisons
  - An example: SSIM (Structural Similarity)
- Perceptual Metrics:
  - Evaluate image quality based on human perception
  - An example: LPIPS (Learned Perceptual Image Patch Similarity)
- No-Reference Metrics:
  - Evaluate image quality without reference images
  - An example: BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator)
- Video Quality Metrics:
  - Take into account temporal aspects of quality degradation
  - An example: VMAF (Video Multi-Method Assessment Fusion)

- UNet: encoder-decoder structure with skip connections
- SRUNet: modified UNet for super-resolution and artefact removal
- Training setup: Generative Adversarial Network (GAN) framework
- Generator loss: combination of LPIPS and SSIM metrics



(a) UNet architecture



(b) SRUNet architecture

Quantization

- Quantization in deep learning: process of reducing the precision of weights and activations of a neural network
- Two main approaches to quantize a deep learning model:
  - Quantization-Aware Training (QAT)
    - Quantization incorporated during training
    - Model learns to be more robust to quantization effects
  - Post-Training Quantization (PTQ)
    - Quantization applied after training the model
    - Model accuracy may be affected

Dataset and Training Setup

- BVI-DVC dataset:
  - Designed for deep video compression tasks
  - Includes 200 frame sequences truncated at the 64th frame
  - Various content types: natural scenes, man-made objects, cityscapes
- Training setup:
  - Models trained on frame patches of 96×96 pixels randomly cropped
  - Model training required ∼72 hours on a single GPU NVIDIA Titan Xp
  - Custom data-loader: to speed up training reducing GPU bottlenecks

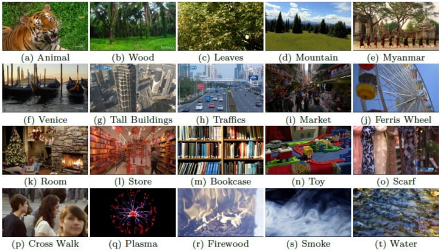


Figure: Some frame examples from the BVI-DVC dataset.

Experiments

- Post-Training Quantization (PTQ) implemented using TensorRT
- Comparison of UNet and SRUNet models with TensorRT-optimized versions (FP32, FP16, INT8)
- Evaluation on 60 test frames using perceptual and traditional metrics
- Quantitative results: Perceptual and traditional metrics show minor differences between optimized and non-optimized models.
- Analysis of inference speed and memory consumption

Quantitative Results: Perceptual Metrics

	LPIPS ↓	DISTS ↓	BRISQUE ↓
UNet	**0.2897 ± 0.0138**	**0.1222 ± 0.0067**	31.1372 ± 1.1690
UNet-FP32	**0.2897 ± 0.0138**	**0.1222 ± 0.0067**	31.1373 ± 1.1684
UNet-FP16	0.2898 ± 0.0138	0.1223 ± 0.0067	31.1383 ± 1.1691
UNet-INT8	0.3041 ± 0.0137	0.1283 ± 0.0066	**29.6849 ± 1.0138**
SRUNet	0.3111 ± 0.0151	**0.1717 ± 0.0047**	27.3738 ± 3.5705
SRUNet-FP32	0.3111 ± 0.0151	**0.1717 ± 0.0047**	27.3736 ± 3.5697
SRUNet-FP16	0.3111 ± 0.0151	**0.1717 ± 0.0047**	27.3790 ± 3.5739
SRUNet-INT8	**0.3068 ± 0.0137**	0.1722 ± 0.0044	**26.1546 ± 3.2273**

Table: Evaluations on perceptual metrics on 60 test frames (mean ± standard deviation).

Quantitative Results: Traditional Metrics

	SSIM $\uparrow$	MS-SSIM $\uparrow$	PSNR $\uparrow$
UNet	**0.8952 $\pm$ 0.0084**	**0.8517 $\pm$ 0.0067**	**21.6506 $\pm$ 0.1269**
UNet-FP32	**0.8952 $\pm$ 0.0084**	**0.8517 $\pm$ 0.0067**	**21.6506 $\pm$ 0.1269**
UNet-FP16	**0.8952 $\pm$ 0.0084**	**0.8517 $\pm$ 0.0067**	**21.6506 $\pm$ 0.1269**
UNet-INT8	0.8941 $\pm$ 0.0084	0.8508 $\pm$ 0.0067	21.6388 $\pm$ 0.1286
SRUNet	**0.8894 $\pm$ 0.0084**	**0.8457 $\pm$ 0.0062**	21.3670 $\pm$ 0.1248
SRUNet-FP32	**0.8894 $\pm$ 0.0084**	**0.8457 $\pm$ 0.0062**	21.3670 $\pm$ 0.1248
SRUNet-FP16	**0.8894 $\pm$ 0.0084**	**0.8457 $\pm$ 0.0062**	**21.3671 $\pm$ 0.1248**
SRUNet-INT8	0.8882 $\pm$ 0.0084	0.8442 $\pm$ 0.0062	21.3320 $\pm$ 0.1224

Table: Evaluations on traditional metrics on 60 test frames (mean $\pm$ standard deviation).

Quantitative Results: Inference Speed

	times [s] $\downarrow$	speedup $\uparrow$
UNet	0.0348 ± 0.0004	
UNet-FP32	0.0279 ± 0.0004	1.25X
UNet-FP16	0.0279 ± 0.0004	1.25X
UNet-INT8	**0.0146 ± 0.0006**	**2.38X**
SRUNet	0.0123 ± 0.0001	
SRUNet-FP32	0.0087 ± 0.0005	1.41X
SRUNet-FP16	0.0087 ± 0.0004	1.41X
SRUNet-INT8	**0.0054 ± 0.0006**	**2.27X**

Table: Evaluation times over 300 runs (mean $\pm$ standard deviation).

Qualitative Results: Buildings

(a) Original Image (384×384)

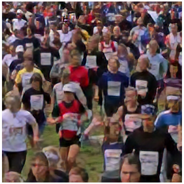
(b) Compressed and Down-scaled (96×96)

(c) Up-scaled using Bilinear Interpolation (384×384)

(d) Up-scaled using SRUNet (384×384)

(e) Up-scaled using SRUNet-INT8 (384×384)

Qualitative Results: Crowd



(a) Original Image (384×384)

(b) Compressed and Down-scaled (96×96)

(c) Up-scaled using Bilinear Interpolation (384×384)

(d) Up-scaled using SRUNet (384×384)

(e) Up-scaled using SRUNet-INT8 (384×384)

Conclusions

- Aim to optimize deep learning models for video quality improvement
- Investigated post-training quantization techniques using TensorRT
- Achieved up to 2.38X speedup and 64.3% size reduction without compromising performance
- Future research:
  - designing efficient NN model architectures
  - co-designing NN architecture and hardware together
  - pruning
  - knowledge distillation
  - exploring different quantization techniques

Thank you, for your attention!

Do you have any questions?

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Appendix

Quantitative Results: VMAF

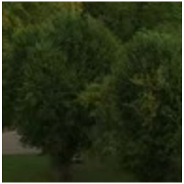
	VMAF (mean) ↑	VMAF (harmonic mean) ↑
UNet	47.71	47.20
UNet-FP32	**47.72**	**47.21**
UNet-FP16	47.71	47.20
UNet-INT8	47.47	46.96
SRUNet	**47.20**	**46.65**
SRUNet-FP32	47.19	46.64
SRUNet-FP16	47.19	**46.65**
SRUNet-INT8	47.18	46.64

Table: VMAF scores on a 120-second-test video.

Qualitative Results: Trees

(a) Original Image (384×384)

(b) Compressed and Down-scaled (96×96)



(c) Up-scaled using Bilinear Interpolation (384×384)

(d) Up-scaled using SRUNet (384×384)

(e) Up-scaled using SRUNet-INT8 (384×384)

LPIPS-Comp: Introduction (1/5)

- LPIPS-Comp: perceptual similarity metric based on deep neural networks
- Trained on a compression-specific perceptual similarity dataset
- Better alignment with human judgement on general compression tasks

VGG-16 and Feed-Forward Process (2/5)

- LPIPS-Comp uses VGG-16 architecture
- ReLU activations after each conv block in the first five layers
- Batch-normalization applied
- Feed-forward performed on VGG-16 for both original (y) and reconstructed image ($\hat{y}$)

Feature Activations and Normalization (3/5)

- $F(y)$ and $F(\hat{y})$ return stacks of feature activations for all layers L
- Unit-normalized in the channel dimension: $z_y^l, z_{\hat{y}}^l \in R^{H_l \times W_l \times C_l}$ where $l \in L$
- H_l, W_l are the spatial dimensions; C_l is the number of channels

Scaling and L2 Distance (4/5)

- $z_y^l, z_{\hat{y}}^l$ are scaled channel-wise with the vector $w_l \in R^{C_l}$
- L2 distance computed and averaged over spatial dimensions
- Channel-wise sum performed

LPIPS-Comp Equation (5/5)

$$\text{LPIPS-Comp}(y, \hat{y}) = \sum_{l} \frac{1}{H_l W_l} \sum_{h,w} \left|\left| w_l \odot \left(z^l_{\hat{y},h,w} - z^l_{y,h,w} \right) \right|\right|_2^2$$

- Weights in F learned for image classification and kept fixed
- w are linear weights learned on a compression-specific similarity dataset