Rate-Distortion-Optimization for Learning-Based Image Compression using Adaptive Hierarchical Autoencoders

Fabian Brand
fabian.brand@fau.de
Chair of Multimedia Communications and Signal Processing

FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

LMS

Rate-Distortion Optimization

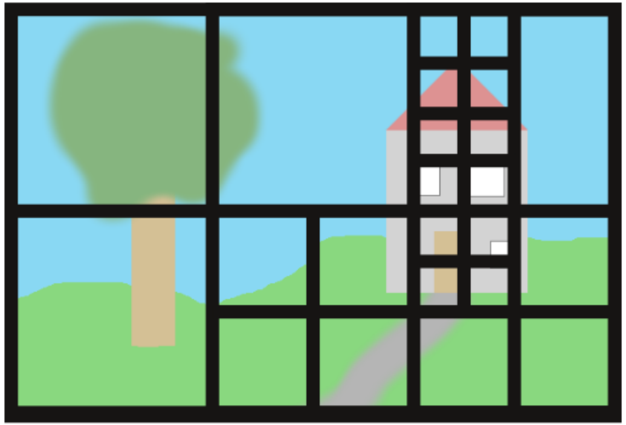
- Multiple decisions in traditional video coding
  - Block partitioning
  - Prediction mode selection
  - Quantization stepsize
  - Many more …
- Selection according to rate distortion cost function

$$J = R + \lambda D$$

- Typically done by testing multiple settings

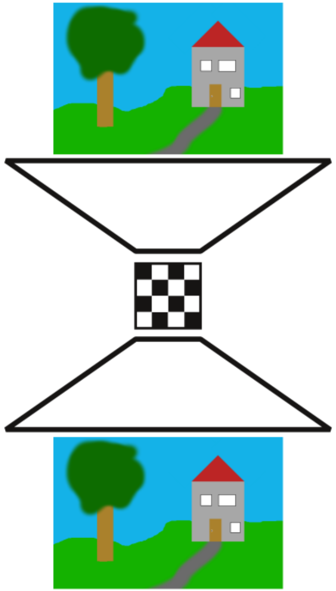
Adaptive Block Partitioning

- Block-based image and video compression (e.g. HEVC, VVC)
- Block-size determines
  - Context for prediction
  - Transform lengths
  - Quantization stepsize
- Rule of thumb:
  - Small blocks for detailed content
  - Large blocks for stationary content
- Adaptive partitioning greatly increases coding efficiency



Learning-Based Image Compression

- Main tool: Autoencoder
- Consists of Encoder network $e(x)$ and decoder network $d(z)$
- Trained on equal input and output, e.g. using MSE
$$L_D = MSE[x; \tilde{x}]$$
- Entropy bottleneck between encoder and decoder
$$L_R = H(\hat{z})$$
- End-to-end training possible



x

$z = e(x)$

$\tilde{z} = Q(z)$

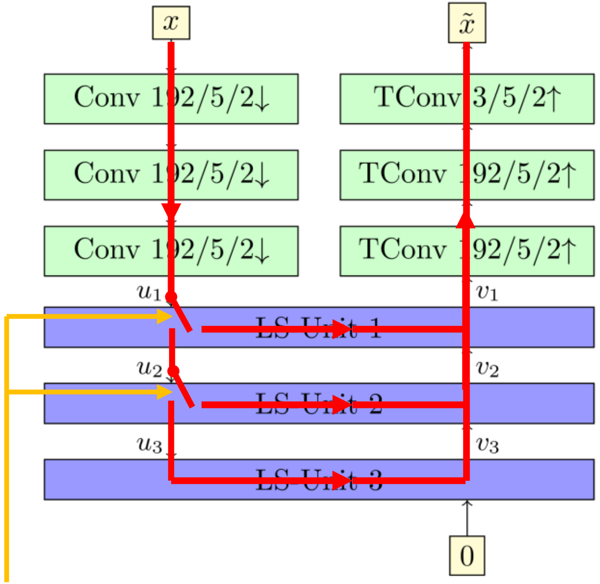
$\tilde{x} = d(\tilde{z})$

Rate-Distortion Optimization in E2E Compression

- Training on joint loss function
$$L = L_D + \lambda L_R$$
- „Static“ RDO
- No free parameters after training
  - No possibility for „dynamic“ RDO

RDONet

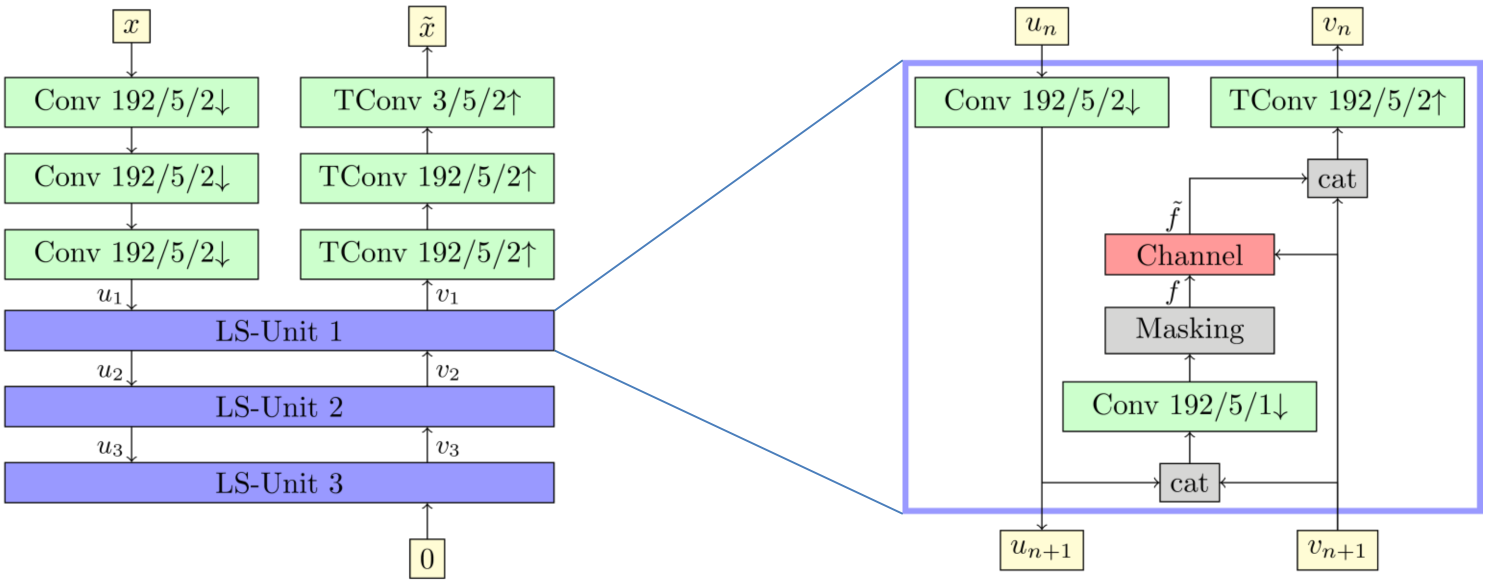
- Compressive Autoencoder capable of coding at adaptive depth
- Compression after 4, 5 or 6 downsampling steps
- Decision on block-level
- Compression as whole image
- No block division
- No block artifacts



Side Information per block

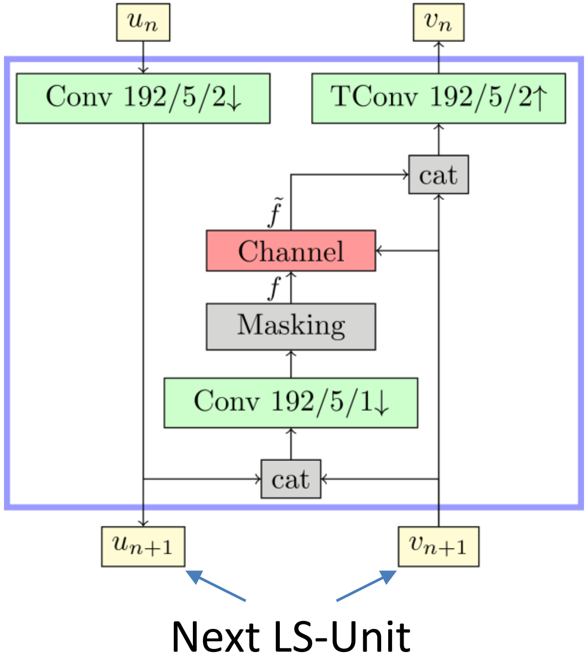
Brand, Fischer, Kaup: „Rate-Distortion-Optimized Image Compression using an adaptive hierarchical autoencoder with conditional hyperprior“, CVPR 2021

Latent Space Units



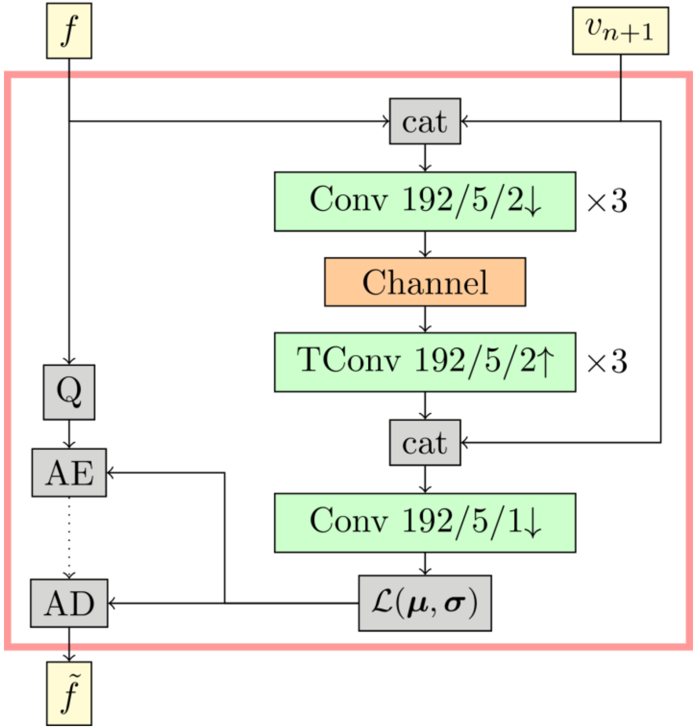
Latent Space Units

- Downsampling on encoder side
- Upsampling on decoder side
- Transmitting masked latent space
- Redundancy from lower LS-Unit
  - Transmit conditional to previous layer



Conditional Hyperprior

- Compression of each latent space with hyperprior
  - Separate autoencoder transmitting pdf for latent space
- Replace hyperprior autoencoder with conditional autoencoder
- Reducing redundancy from previous latent space



Summary of Network

Coding on different levels of autoencoder possible

Level externally adjustable on block-level

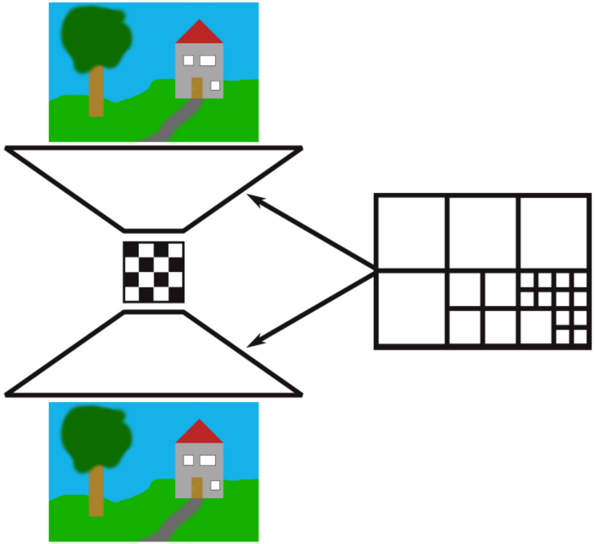
Conditional coding to reduce redundancy between levels

Rate-Distortion Optimization in E2E Compression

- Training on joint loss function

$$L = L_D + \lambda L_R$$

- „Static“ RDO
- ~~No free parameters after training~~
  - ~~No possibility for „dynamic“ RDO~~
- Externally controlled depth
- Test different depth configurations and pick best



RDO Search

- Initialize image coding with lowest latent space
- Test if higher latent space yields better RD-behavior
- Optimizing each 64x64 area individually
  - Global search not feasible
  - Global optimum not found
- Solution: 2-pass RDO
  - Initialize with result of first pass

Experiments

Training

- Train on CLIC Intra + DIV2K + TECNICK
- Random choice of LS depth
- Train for 2000 epochs
- Train on MS-SSIM and MSE
  - MSE needed for stability

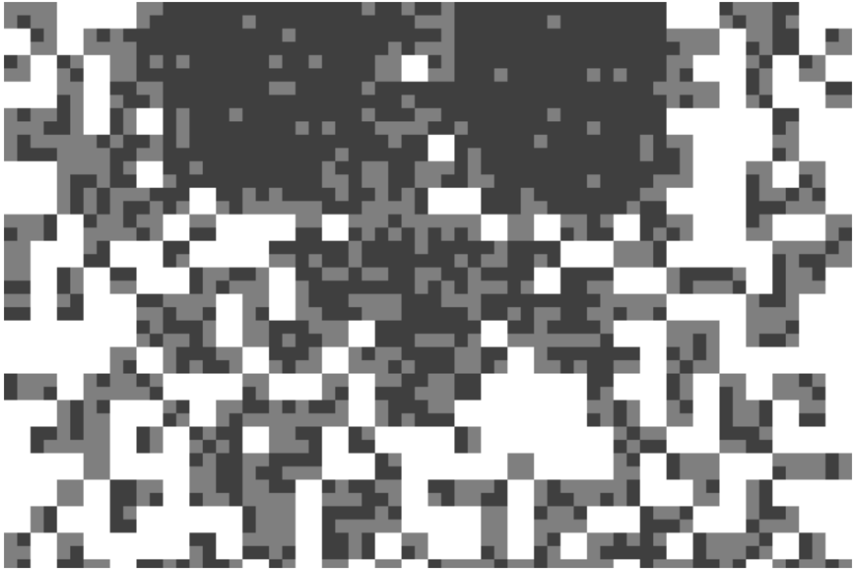
$$L_{\text{train}} = D_{\text{ms-ssim}} + 0.1 \cdot D_{\text{mse}} + \lambda_t R$$

Test

- Evaluate on CLIC Intra test set
- Compare 1-pass and 2-pass RDO
- Compare against standard 4 layer autoencoder with hyperprior and context model
- MS-SSIM as distortion metric

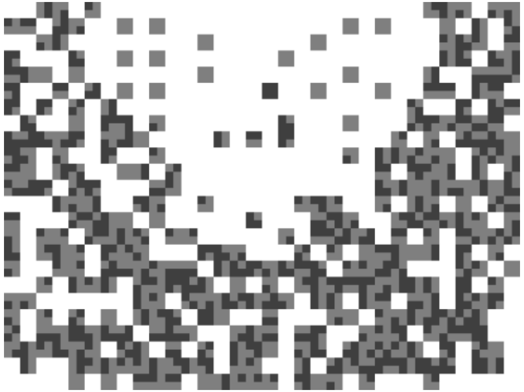
$$L_{\text{RDO}} = D_{\text{ms-ssim}} + \lambda_e R$$

Visual Example



Example Block Partitioning (Dark: Small blocks, high level)

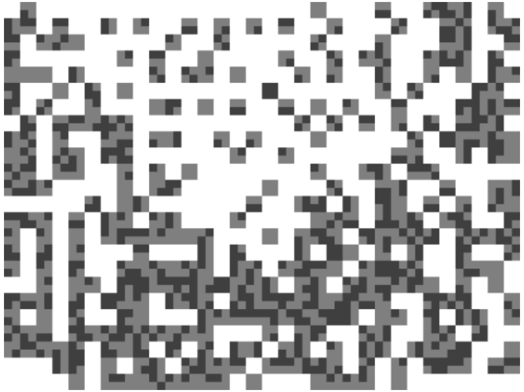
Visual Example



$\lambda_e = 1$

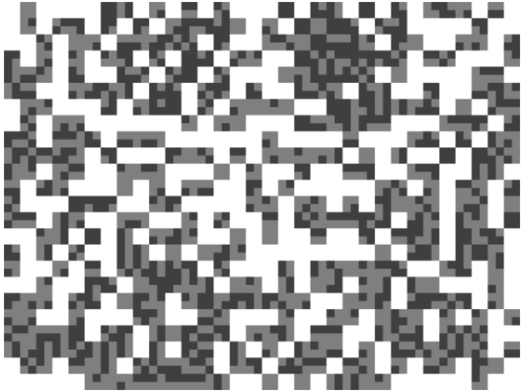
$r = 0.096bpp$

Visual Example



$\lambda_e = 0.5$ $r = 0.104bpp$

Visual Example

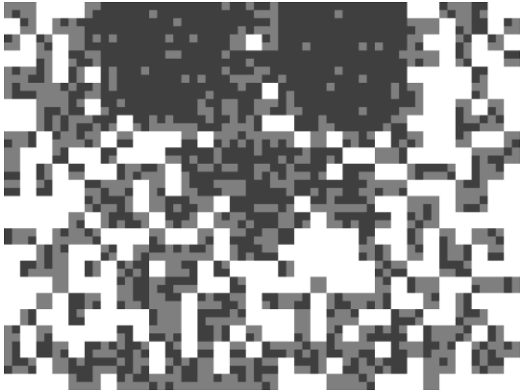


$\lambda_e = 0.25$ $\qquad r = 0.119bpp$

Visual Example

$\lambda_e = 0.125$ $r = 0.136bpp$

Visual Example



$\lambda_e = 0.0625$ $r = 0.141bpp$

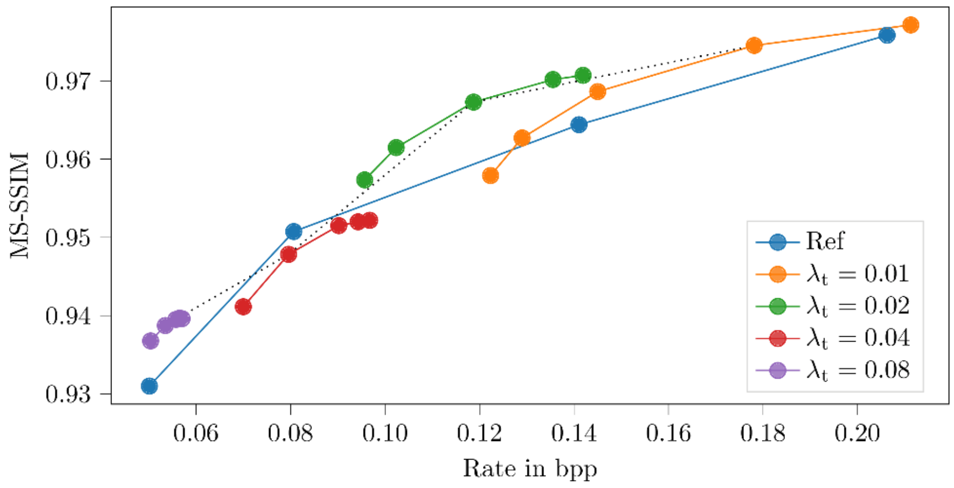
Visual Example

Standard Autoencoder

$r = 0.141bpp$

Results

- Five rate-points per model
  - RDO allows multiple rate points per model
  - Optimal behavior if λ match in training and RDO
- Pick one rate point per model for final evaluation



Results

- Rate savings over compression without RDO
- Additional gains by 2-pass RDO
- 7.7% rate saving on average
- Up to 22.5% for single images

	1-pass	2-pass
Worst Case	+7,5%	+3.5%
Best Case	-18.8%	-22.5%
Average	-4.1%	-7.7%

BD-Rates for entire CLIC validation set

Conclusion

- RDONet enables RDO similar to adaptive block partitioning
- Saving 7.7% rate compared to standard autoencoder
- Increase visual quality by adaptive bit allocation
- Transferring concept from traditional video compression to end-to-end image coding