
Fast Partitioning for VVC Intra-Picture Encoding With a CNN Minimizing the Rate-Distortion-Time Cost

Gerhard Tech, Jonathan Pfaff, Heiko Schwarz, Philipp Helle,
Adam Wieckowski, Detlev Marpe, and Thomas Wiegand

Motivation

■ Versatile Video Coding (VVC)

- New coding tools e.g. for intra-picture coding:

multi-type tree (MTT), intra sub-block partitions (ISP), matrix-based intra prediction (MIP), extended number of directional modes, multi-reference line (MRL), low-frequency non-separable transform (LFNST), multiple transform select (MTS) ...

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■ Requirement: Encoder selects efficient coding modes

- Rate-distortion optimization (RDO)

- Encode a block B with different partitioning, prediction, and transform mode combinations
- Select the modes providing the minimal Lagrangian rate-distortion (RD) cost

- Problem: Limited encoding time; not all combinations can be tested

→ Some modes must be skipped without testing

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■ Which modes should the encoder skip?

- Optimally: Reduce encoding time, while not increasing the RD cost

→ Subject of this presentation: Doing this by skipping MTT partitioning modes

Outline

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 - VVC partitioning
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- How to estimate the optimal parameters practically?
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 - Training data generation
 - Loss function in training

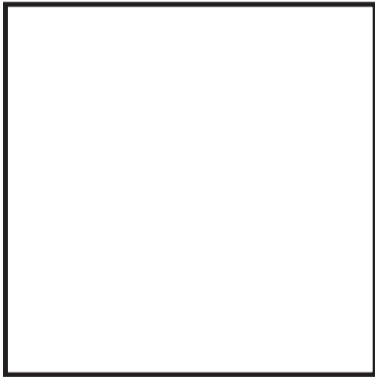
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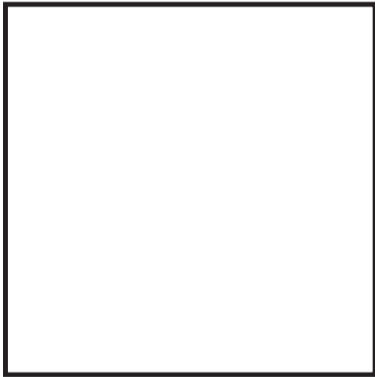
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- Summary and Conclusion

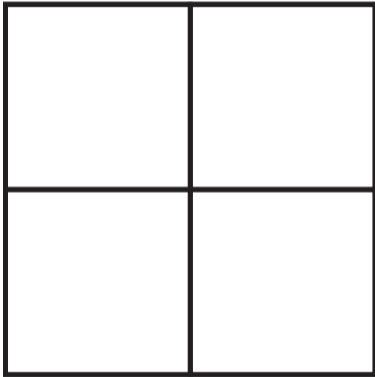
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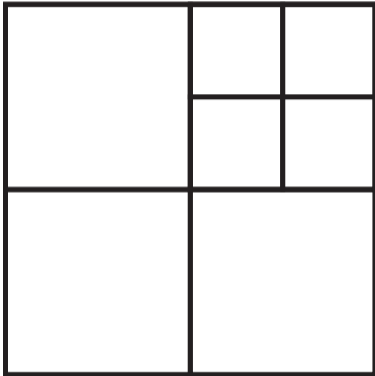
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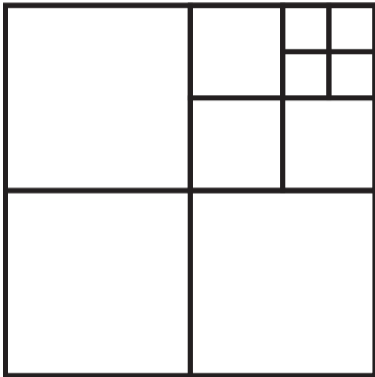
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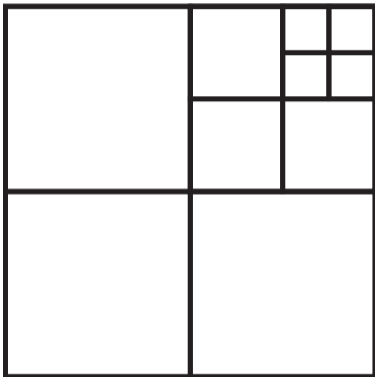


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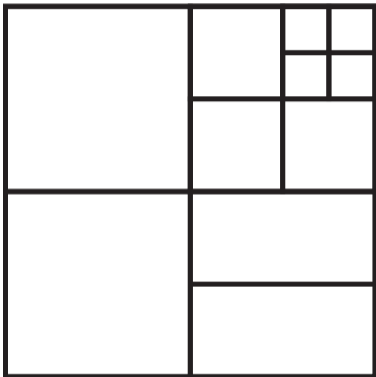


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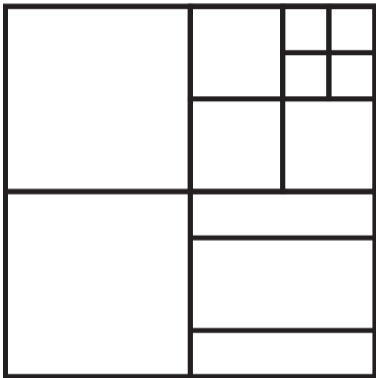




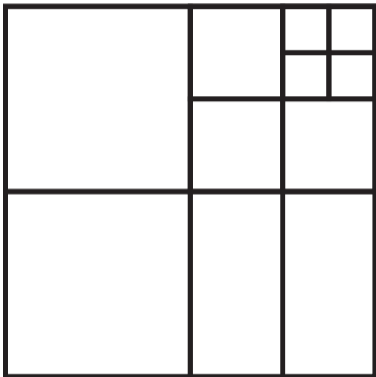
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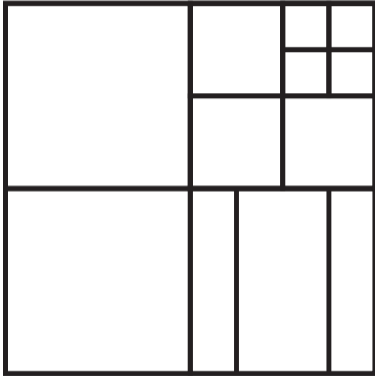
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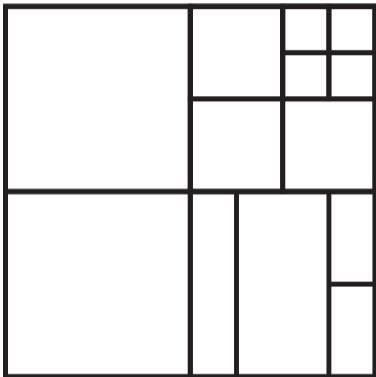
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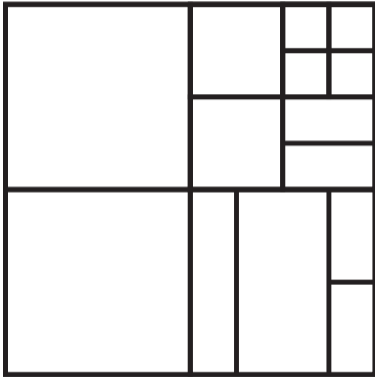
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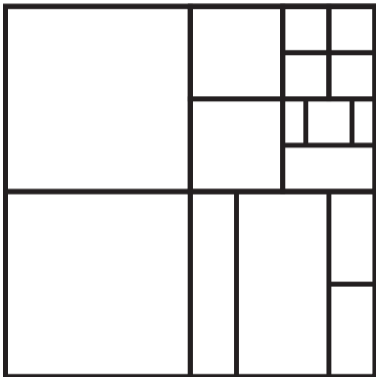
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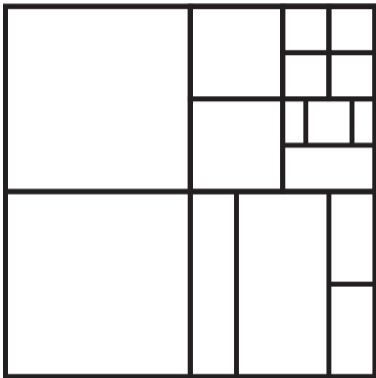
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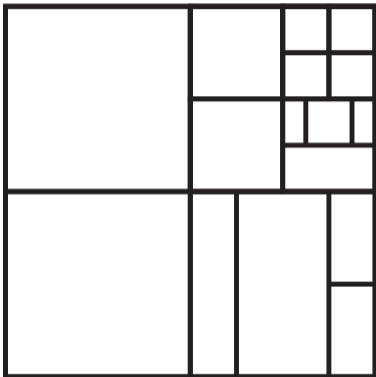
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 - Various options to adapt to the content
 - However: Most options irrelevant
- Idea:
- Skip partitioning modes based on the block content without testing
 - Introduce parameters controlling which modes are skipped

Parameters

- Idea: Limit the size of tested MTT partitionings for 32×32 blocks with two parameters

$$\mathbf{P} = \begin{pmatrix} p_H \\ p_V \end{pmatrix}$$

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- Skip testing an MTT split if any resulting sub-block would have
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 - with N_q denoting the size of the MTT's quad-tree leaf node

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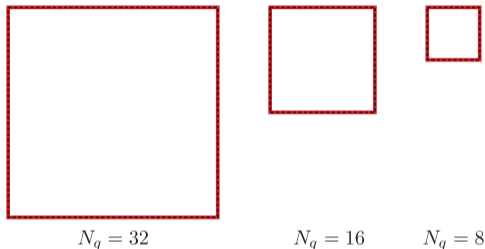
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Partitioning Restrictions

$$\mathbf{P} = \begin{pmatrix} p_H \\ p_V \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$



— Minimum allowed MTT-subdivision size
- - - - - QT leaf node size

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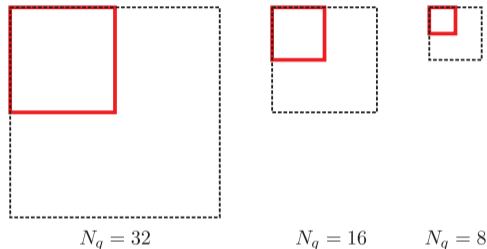
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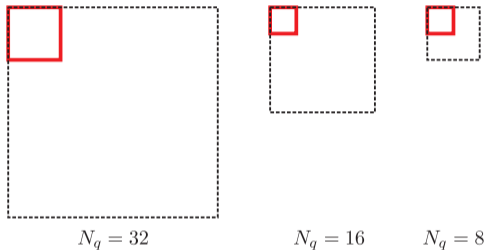
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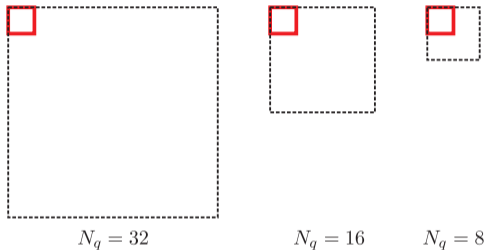
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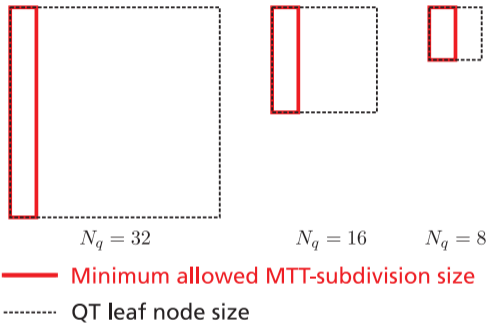
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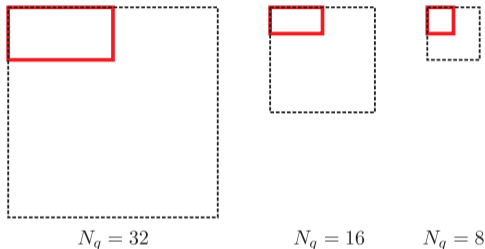
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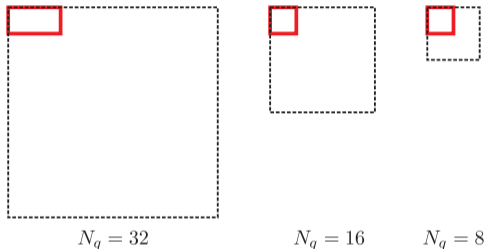
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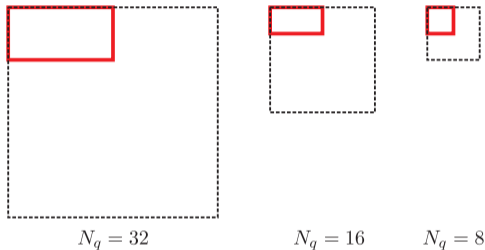
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- Adaptation to block content possible

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 - Per block B , select the parameter \mathbf{P} that produces the minimal rate-distortion-time cost K :

$$K(\mathbf{P}) = \underbrace{D(\mathbf{P}) + \lambda \cdot R(\mathbf{P})}_{\text{rate-distortion cost } J(\mathbf{P})} + \underbrace{\mu \cdot T(\mathbf{P})}_{\text{time cost}}$$

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- When $K(\mathbf{P})$ is independent for different B , block-wise minimization also minimizes the overall RDT cost

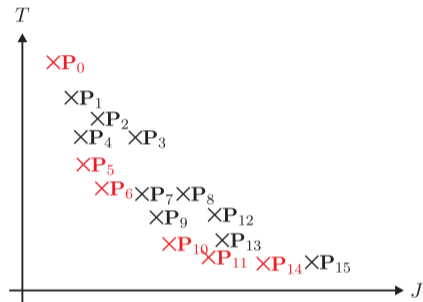
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Basic Idea

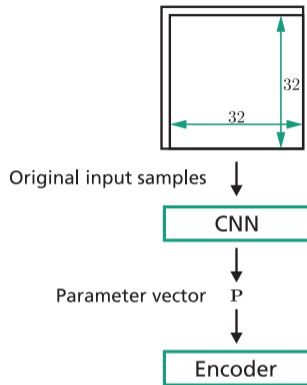
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- Train the CNN such that \mathbf{P} minimize the RDT cost

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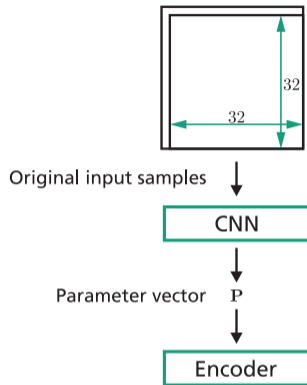
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■ Training Approach

- Training data generation:
 - Perform the Lagrangian method
 - Record the occurring RDT-cost
- In training:
 - Use the stored RDT cost to compute the training loss

CNN-based Parameter Estimation

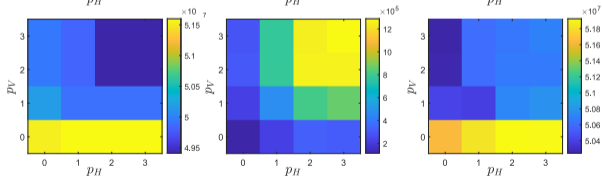
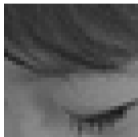
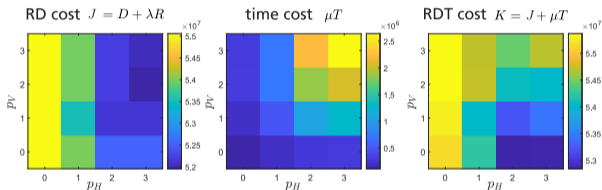


- Encode training sequences, for each 32×32 block B :
 - Encode B with all \mathbf{P}
 - Store the occurring RDT cost $K(\mathbf{P})$
 - Select \mathbf{P} providing the minimum $K(\mathbf{P})$ and continue based on its encoder state

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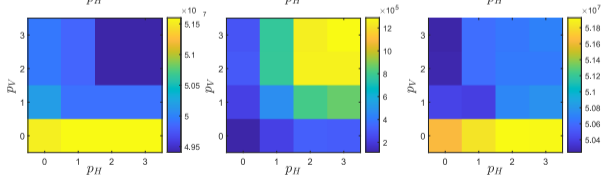
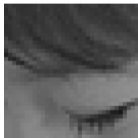
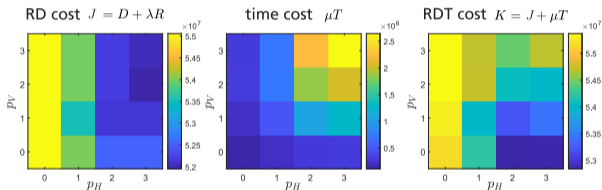
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■ Lagrange parameters:

- λ : encoder default for QP
- μ : determines encoding time

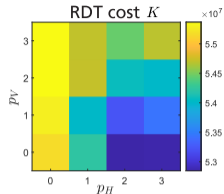
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 - Interpret the two floating point CNN outputs as p_H and p_V
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 - Requires derivatives of loss function with respect to p_H and p_V
 - Problem: K sampled at integer values; derivatives do not exist

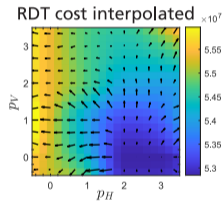
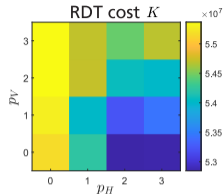
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- Solution
 - Model derivatives using an interpolated loss function

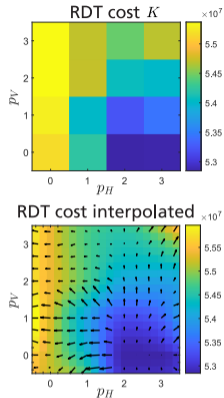
CNN-based Parameter Estimation



Loss Function in Training

- Objective: Minimize the RDT cost of estimated parameters
- Approach
 - Interpret the two floating point CNN outputs as p_H and p_V
 - Gradient descent method
 - Requires derivatives of loss function with respect to p_H and p_V
 - Problem: K sampled at integer values; derivatives do not exist
- Solution
 - Model derivatives using an interpolated loss function
- If $0 \leq p_H \leq 3$ and $0 \leq p_V \leq 3$
 - Horizontal and vertical interpolation using cubic hermite B-splines
 - Advantage: shape preserving; produces no local minima

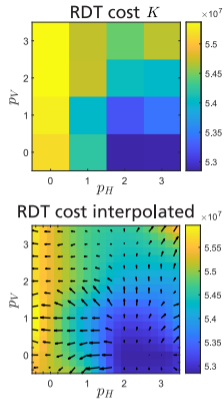
CNN-based Parameter Estimation

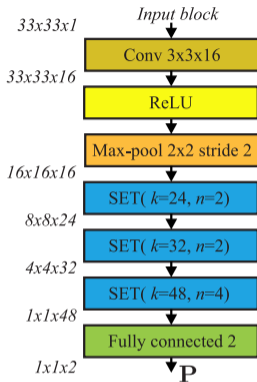


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- Otherwise
 - Artificial gradient pointing away from the sampled area
 - Ensures that the gradient descent method converges back

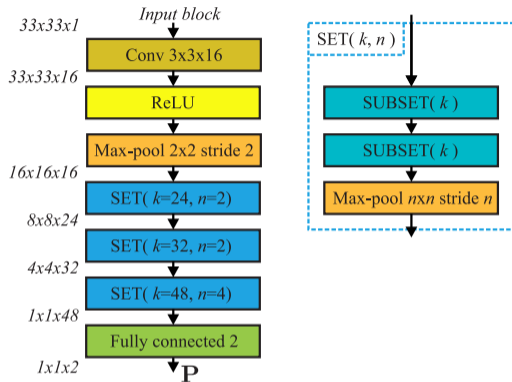
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- Corresponds to CNN of Galpin (2019) and Tissier (2020) [inspired by ResNet]

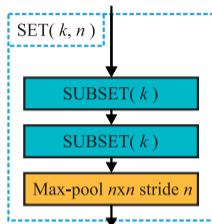
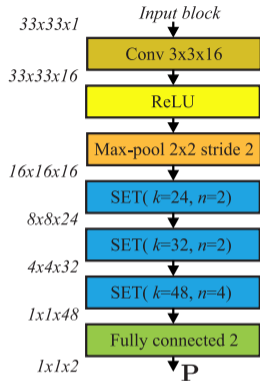
The CNN



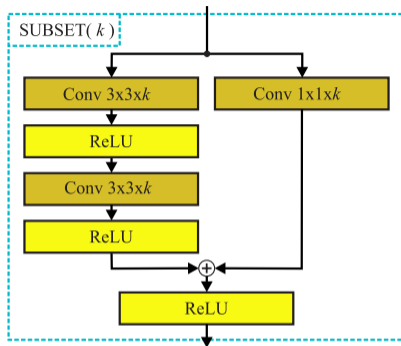
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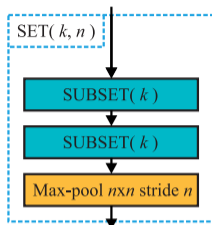
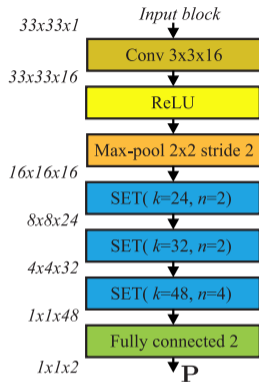


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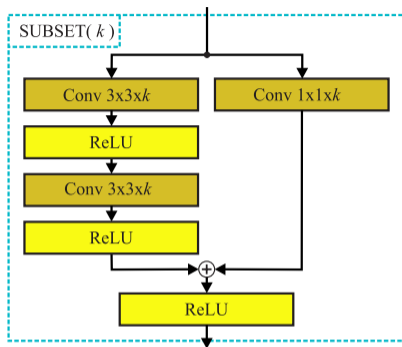


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The CNN



CNN-based Parameter Estimation



■ Corresponds to CNN of Galpin (2019) and Tissier (2020) [inspired by ResNet]

■ Modifications:

- Max pooling size changed to input 33×33 instead of 65×65 blocks
- 2 outputs instead of 480

Conditions

■ Training

- 24 million training patches
- 22 epochs
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- 6 Encoding time points
- 4 QPs: 22, 27, 32, and 37
- An individual μ for each CNN, such that
 - for all QPs of an encoding time point:
 - approximately the same encoding time reduction (in percent)

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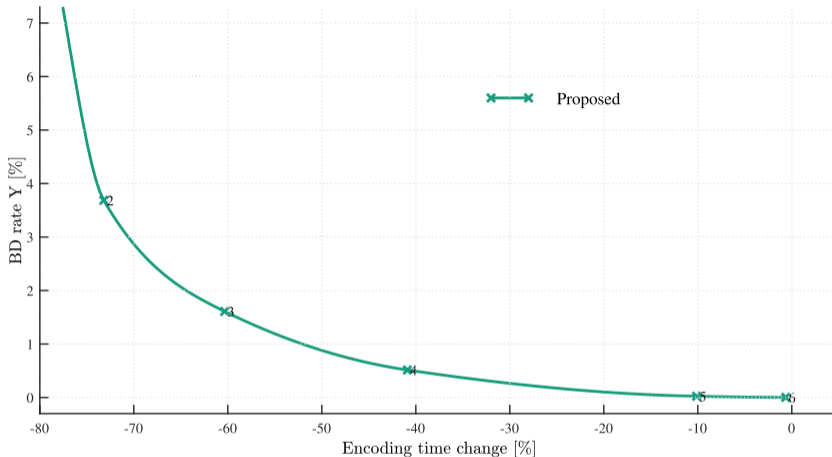
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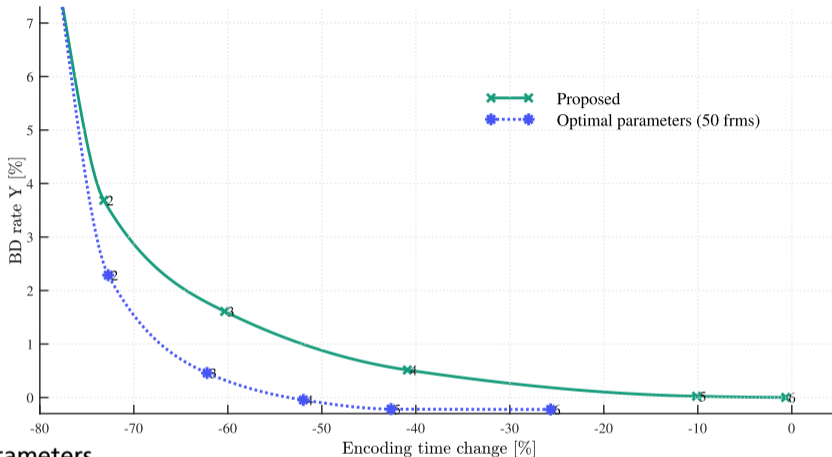
■ Coding conditions

- JVET's test conditions for All-Intra Coding
- CNN run-times included
- Basis and anchor: VTM-7.0
- No default optimizations disabled



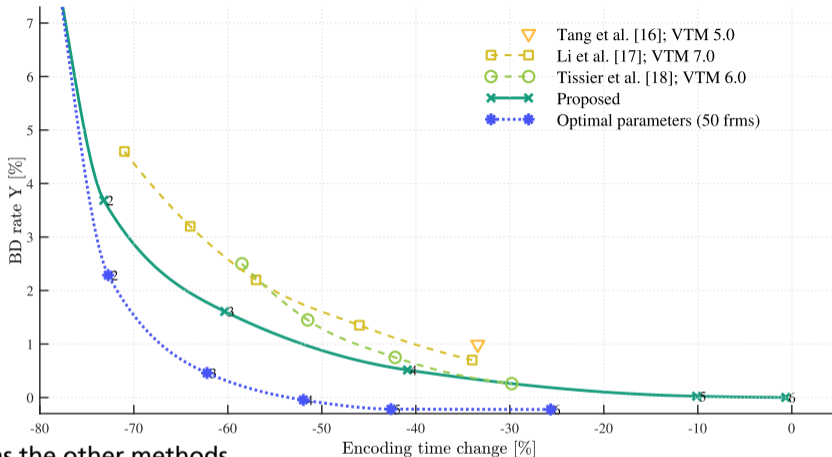
■ Results

- 10% encoding time reduction, neglectable BD rate increase
- 50% encoding time reductions, 0.9% BD rate increase
- 73% encoding time reductions, 3.7% BD rate increase



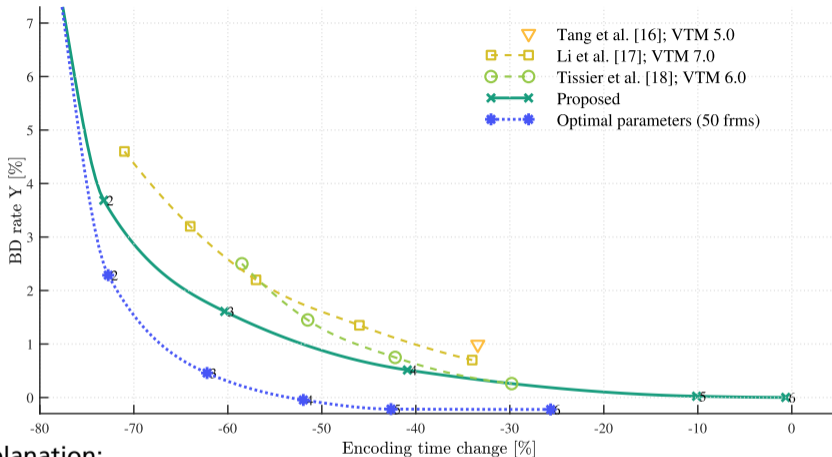
■ Optimal parameters

- Hypothetical result
- Gap: CNN estimation not perfect
- Potential for further improvements, e.g. advanced CNN layouts



■ Outperforms the other methods

- Other: great number of parameters with much finer granularity.
- Our: only estimates two parameters for a 32×32 block



■ Possible explanation:

- Advanced loss function
- Can explore the actual RDT cost for the full parameter space offline
- Trades off estimation flexibility against estimation accuracy

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 - CNN with original samples as input
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 - CNN with original samples as input
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- Conclusions
 - We outperform other methods although using only two parameters for large blocks
 - Our loss function models the RDT cost accurately
 - Might be better to optimize fewer parameters, but with an exact loss function

Thank you for your attention!

■ Any questions?

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