Overview of technologies considered in JVET's neural network-based video coding exploration

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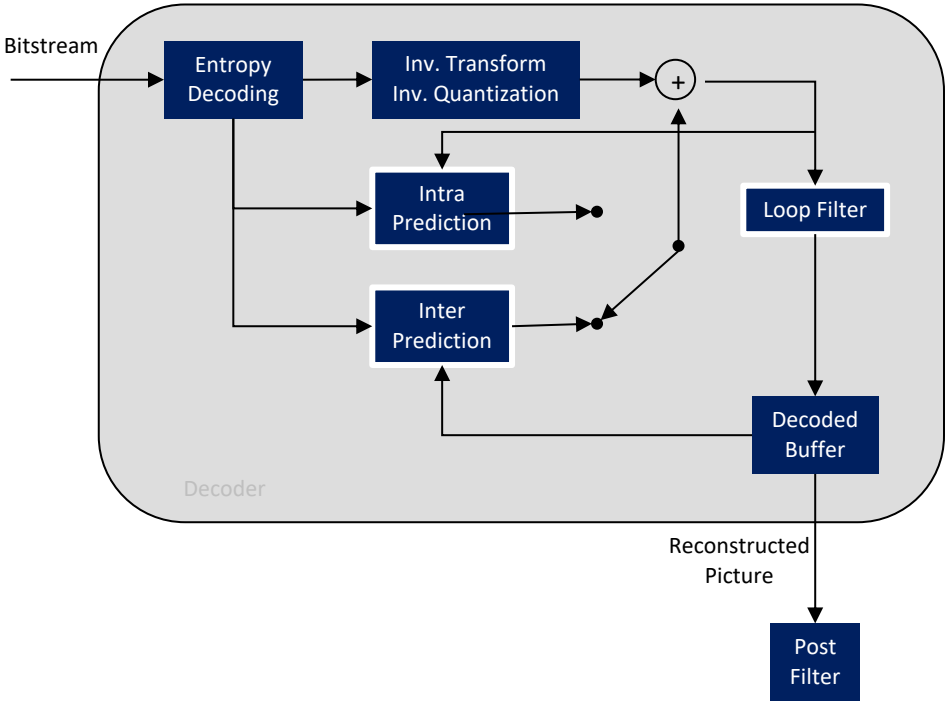
Introduction

- The Joint Video Experts Team (JVET) began formal exploration experiments studying neural network-based video coding in October 2020.
- Interest in this activity has been consistent, and JVET has received more than 110 technical inputs related to the topic in 2021 and 2022.
- The goal of this presentation is to give an overview of technologies being proposed and studied.

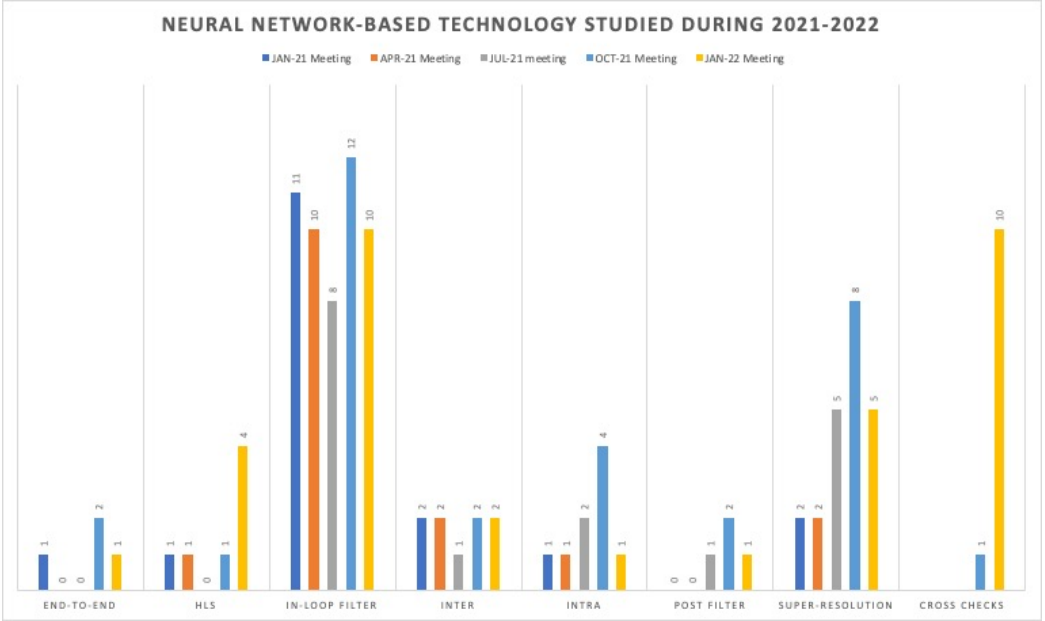
Categorization

- Organizing the survey is helped by categorizing the technologies
- Three major areas of work in JVET:
  1. Replacing existing VVC coding tools (or enhancing them)
  2. Introducing post-filtering operations
  3. End-to-end solutions that do not rely on VVC
- Tool replacement (or enhancement) is primarily focused on:
  1. In-loop filtering
  2. Super-resolution
  3. Intra-Prediction
  4. Inter-Prediction



Categorization

- Focus of JVET activity
  - Activity in all categories
  - Largest number of contributions are in:
    - In-loop filtering
      - 51 contributions
      - ~43% of technical input
    - Super-resolution
      - 22 contributions
  - Additional observation
    - Technical overlap between in-loop filter, post filter and super-resolution methods



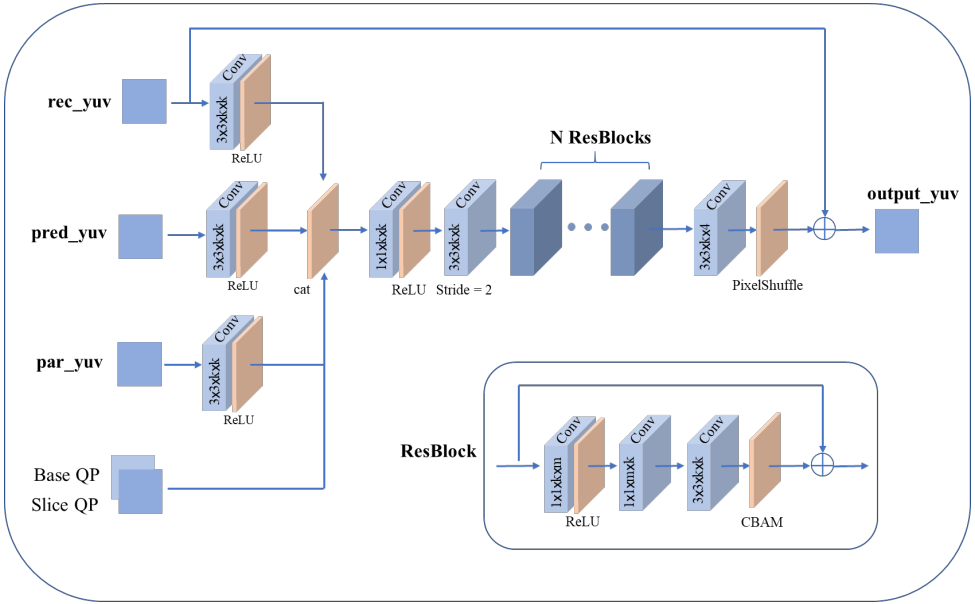
Overview

- Overview
  - The rest of the presentation will be organized as follows:
    - Filtering methods
      - In-loop filtering
      - Post-Filtering
      - Super-Resolution
    - Intra-prediction methods
    - Inter-prediction methods
    - End-to-end methods
    - NN environments
    - Conclusions and more information

Filtering Methods: In-Loop Filtering

Loop Filtering

- Example of Loop Filtering Technology
  - Inputs
    - Reconstructed samples
    - Predicted samples
    - Partition parameters
    - Quantization parameters
  - Common features
    - Sequence of CNNs
    - Residual blocks
    - Shorter and longer skip connections
    - Attention mechanisms



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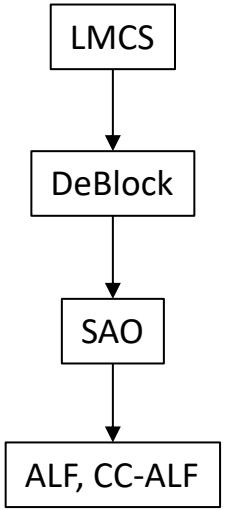
N = 8
Channels = 64
Patch size = 144x144

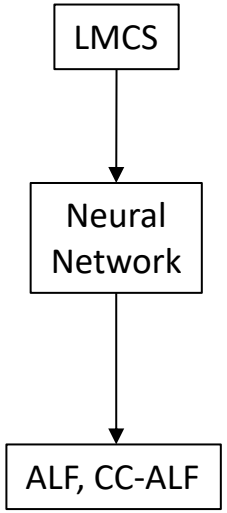
Loop Filtering

- Loop Filtering
  - Location of the neural network within the loop filter is an area of exploration
  - VVC design contains four major in-loop blocks
    - LMCS (Luma Mapping and Chroma Scaling)
    - Deblocking
    - SAO (Sample Adaptive Offset)
    - ALF (Adaptive Loop Filter)
  - Investigations
    - Adding neural networks to the in-loop process
    - Replacing elements of the in-loop blocks

VVC Loop Filter

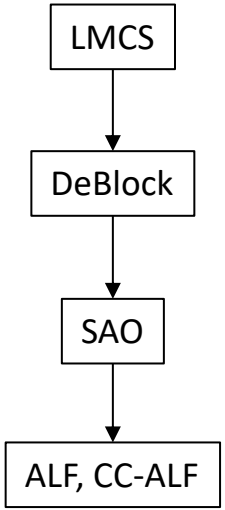


Example NN Loop Filter

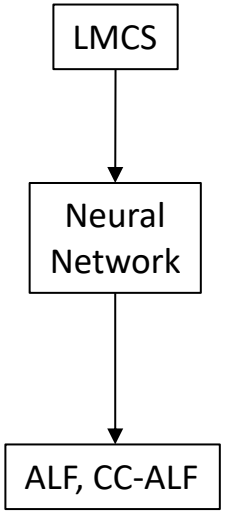


Loop Filtering

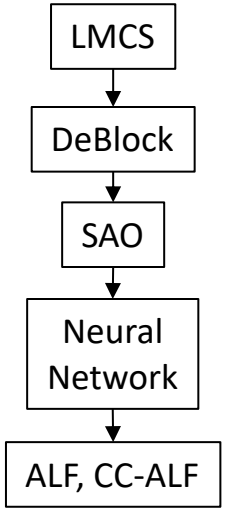
VVC Loop Filter



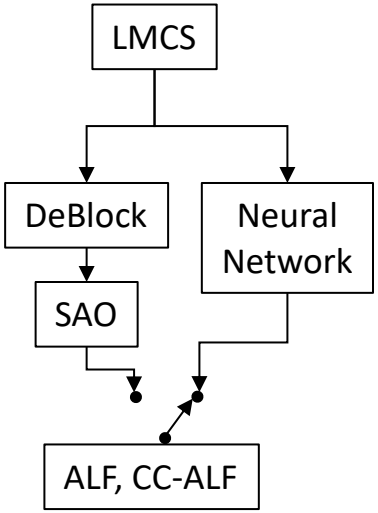
Example NN Loop Filter



Example NN Loop Filter

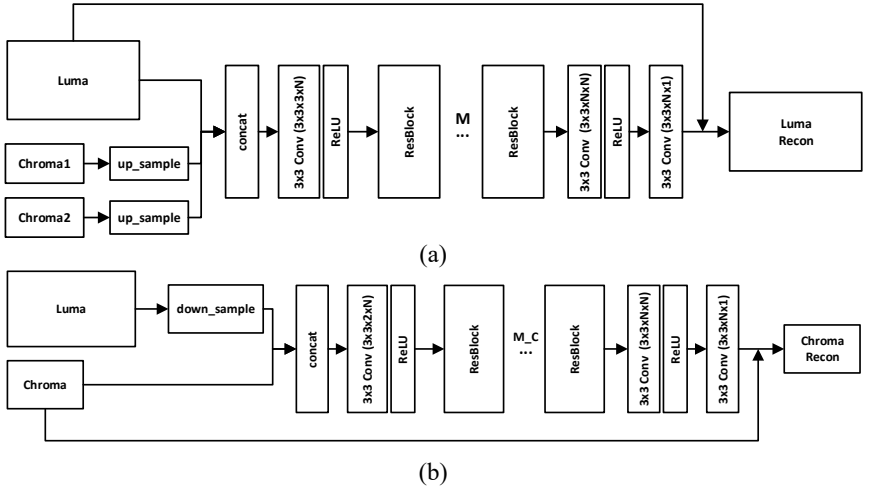


Example NN Loop Filter



Loop Filtering

- Additional aspects under study
  - Benefit of cross channel correlation
  - Model parameter switching
  - Networks generally pre-trained with different weights loaded depending on conditions, such as:
    - Slice type
    - Chroma type
    - Base QP



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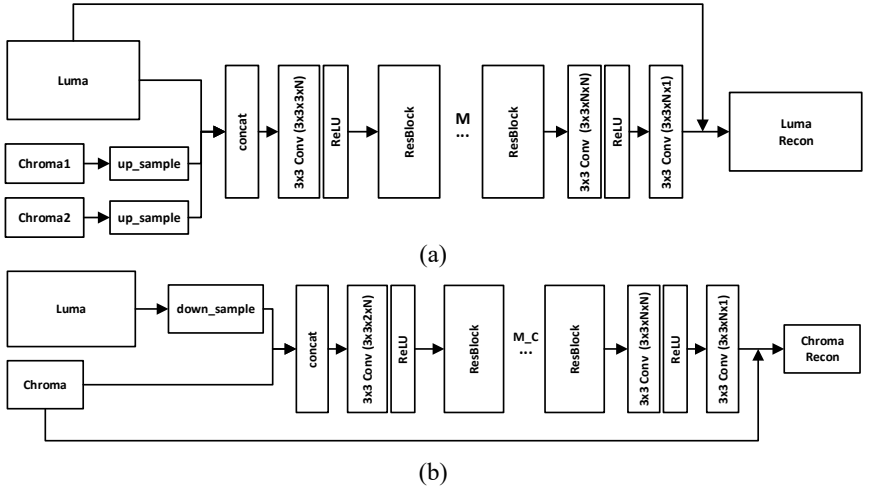
Loop Filtering

- Additional aspects under study
  - Switching granularity
    - Enable network per-frame
    - Enable network per-slice
    - Enable network per-block
    - Signal from candidate set
  - Switching precision
    - Binary switching
    - Signaling residual scaling factors
  - Network architectures
    - U-Nets
    - Transformers



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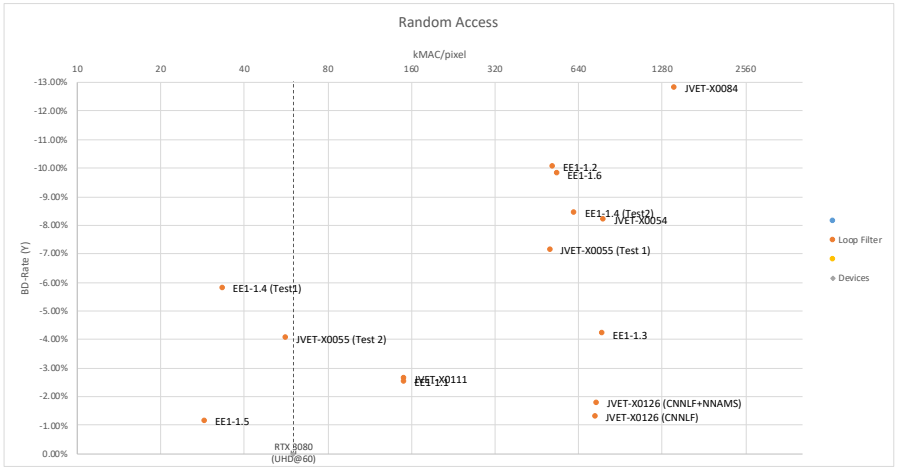
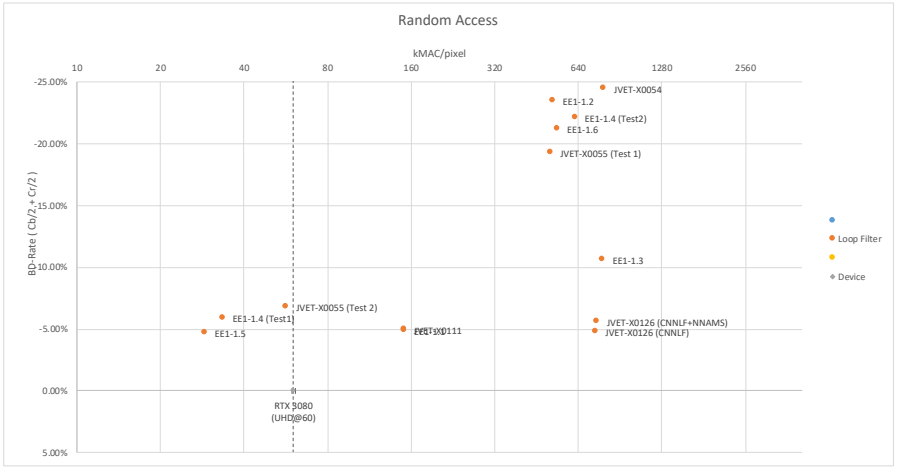
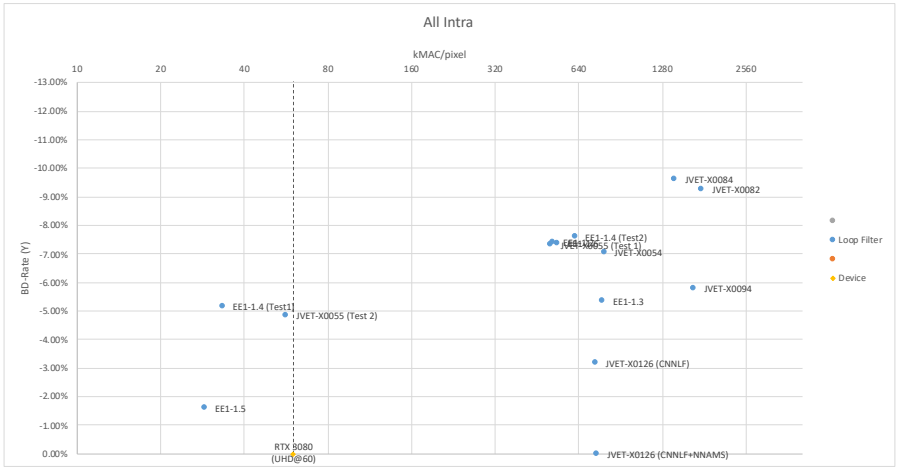
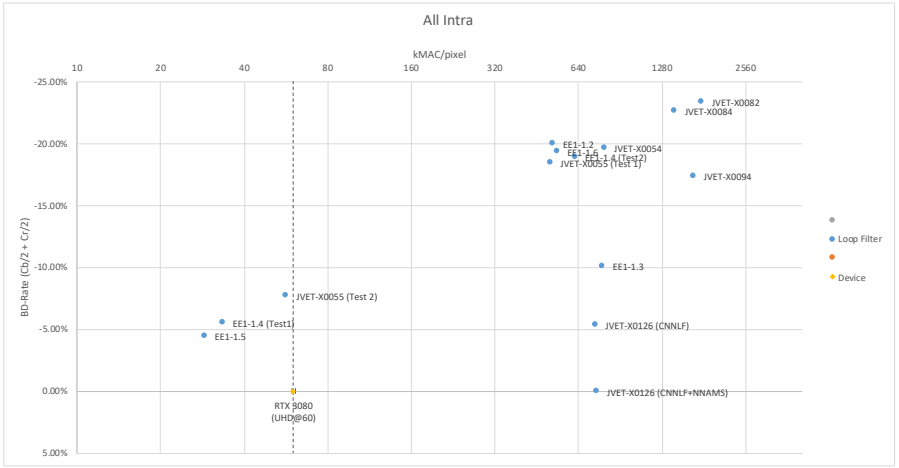
Loop Filtering



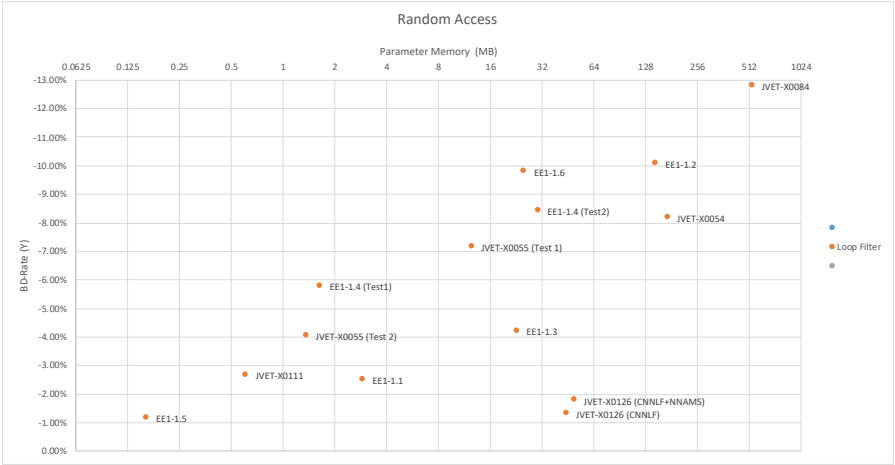


Loop Filtering





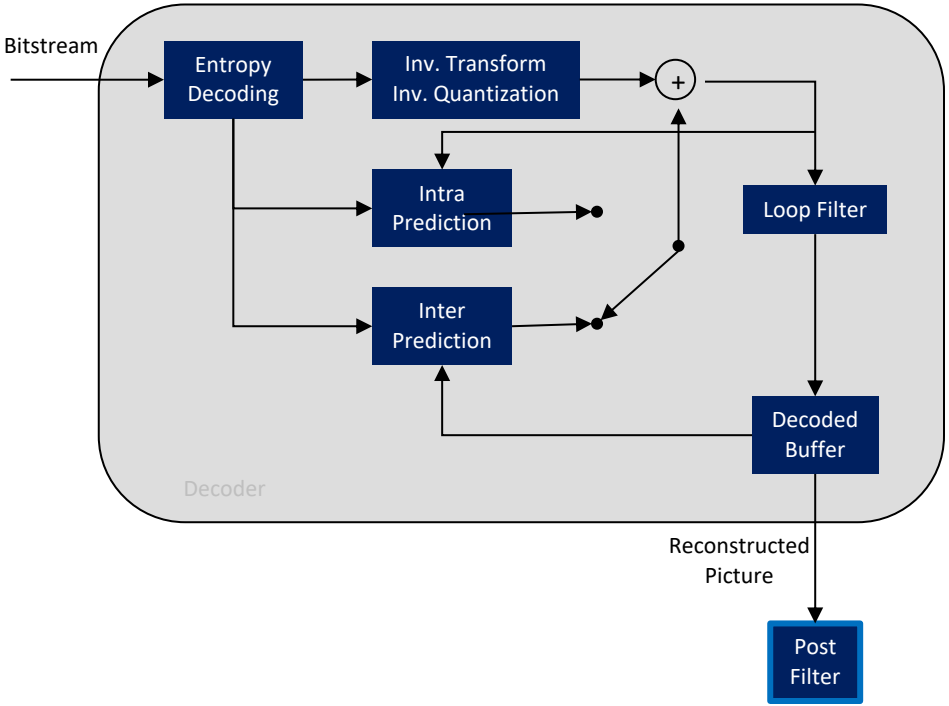
Loop Filtering



Filtering Methods: Post Filtering

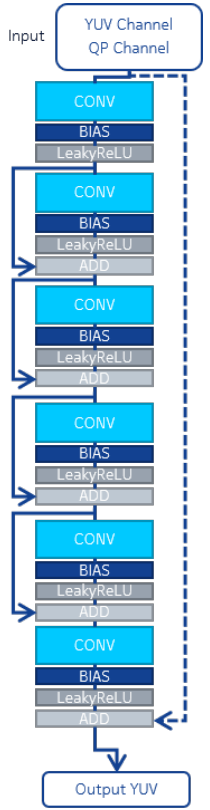
Post-Filtering

- Post-Filtering
  - Similar to loop filtering technology
  - Major conceptual difference is that the neural network is placed outside the coding loop



Post-Filtering

- Post-Filtering
  - Example technology
    - Sequence of CNNs
    - ResNet blocks
    - Shorter and longer skip connections
    - Reconstructed block, neighboring samples, QP information and boundary strength as input
  - Additional features
    - Model is pre-trained
    - Scaling parameters transmitted in bit-stream
    - Bias terms are refined and transmitted in the bit-stream



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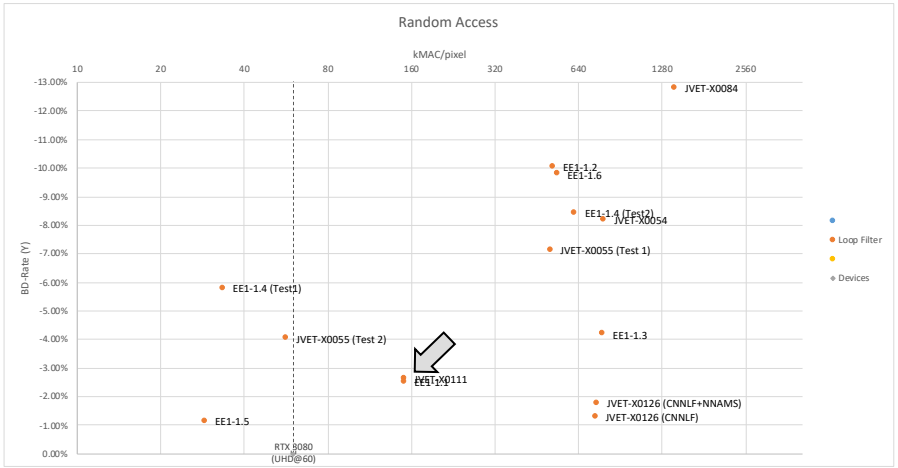
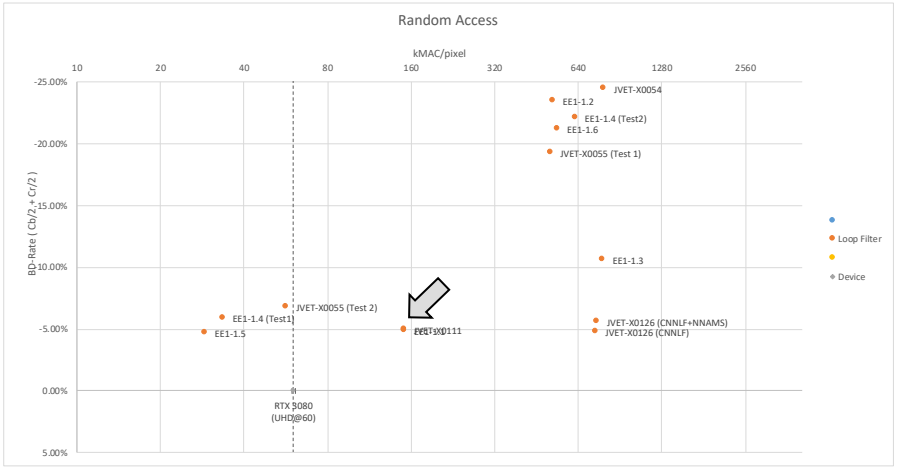
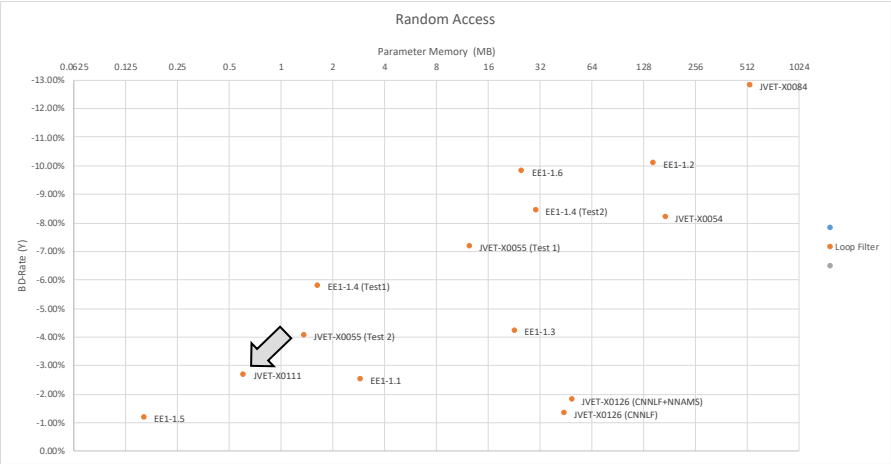
Post-Filtering





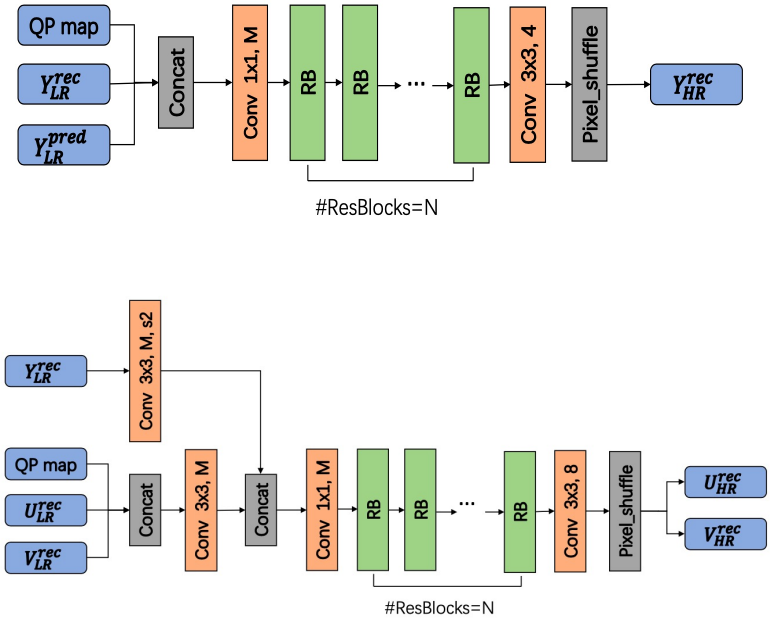
Post-Filtering



Filtering Methods: Super-Resolution

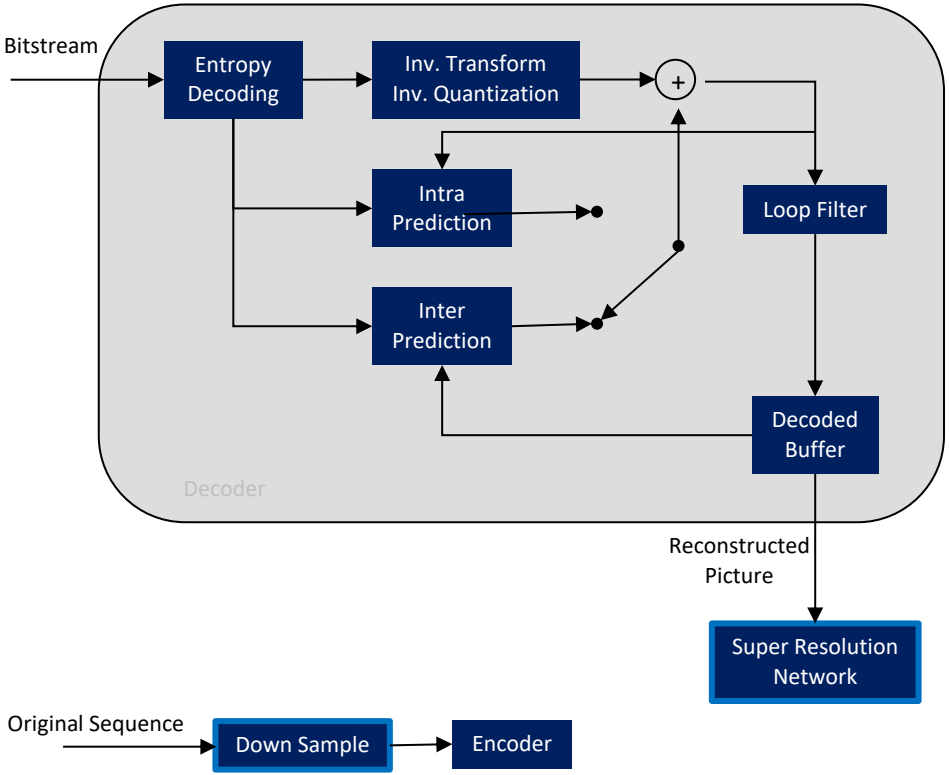
Super-Resolution

- Super-resolution
  - Viewed as a replacement of Reference Picture Resampling (RPR) in VVC
  - RPR allows for changing the resolution of the sequence within a bit-stream
  - Neural network solutions are proposed to replace the RPR operation
  - Features are similar to in-loop filtering and post-processing approaches under study
    - Sequence of CNNs
    - ResNets
    - Longer term skip connections and attention less common (currently)



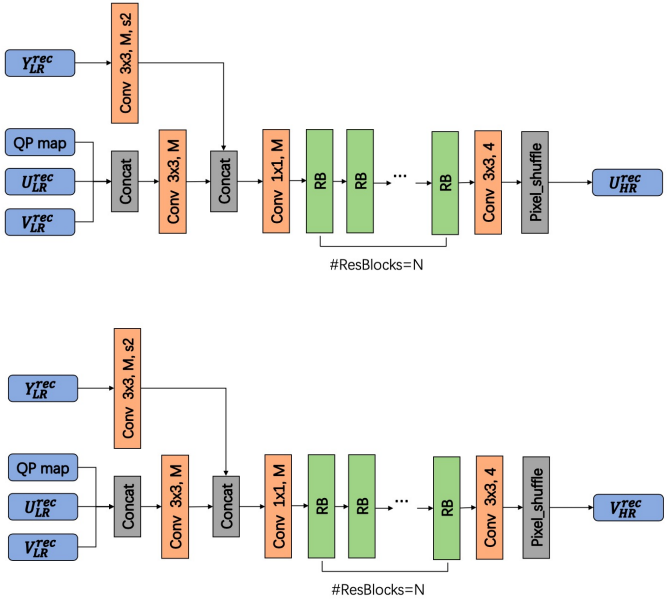
Super-Resolution

- Network placement
  - Super-resolution experiments do not incorporate switching resolution within a sequence
  - In practice, this means that the super-resolution network are located as a post-filter
    - Input sequence is down-sampled and compressed using VVC
    - Reconstructed sequence is upsampled using super-resolution network



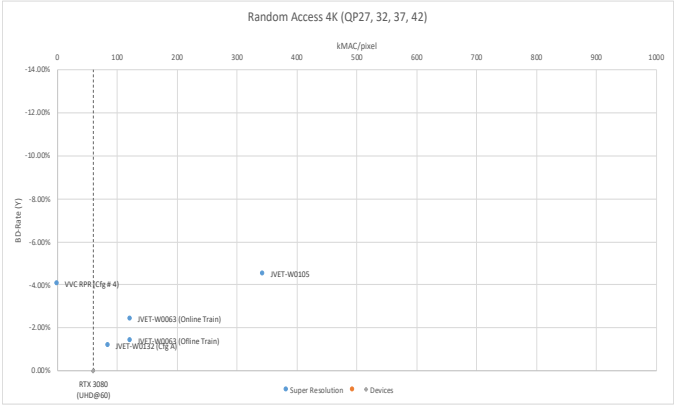
Super-Resolution

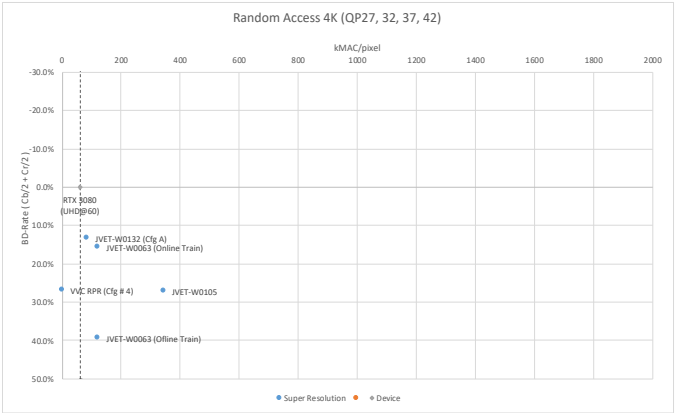
- Additional aspects under study
  - Use of different networks for chroma channels
    - Luma-chroma balance
  - Number of parameters and networks
  - Resolution control
    - Dynamic down-sampling to maximize coding efficiency
    - Fixed down-sampling for backwards compatibility constraint (e.g., 8K support)



Super-Resolution

- Performance
  - Observation that super-resolution techniques primarily work at higher resolutions and/or lower bit-rates
  - Majority of data provided to JVET focuses on low bit-rate 4K/UHD applications
    - July meeting
      - Luma gain of 4%
      - Chroma loss of 40%
    - October and January meeting
      - Average chroma loss decreased but still isolated issues

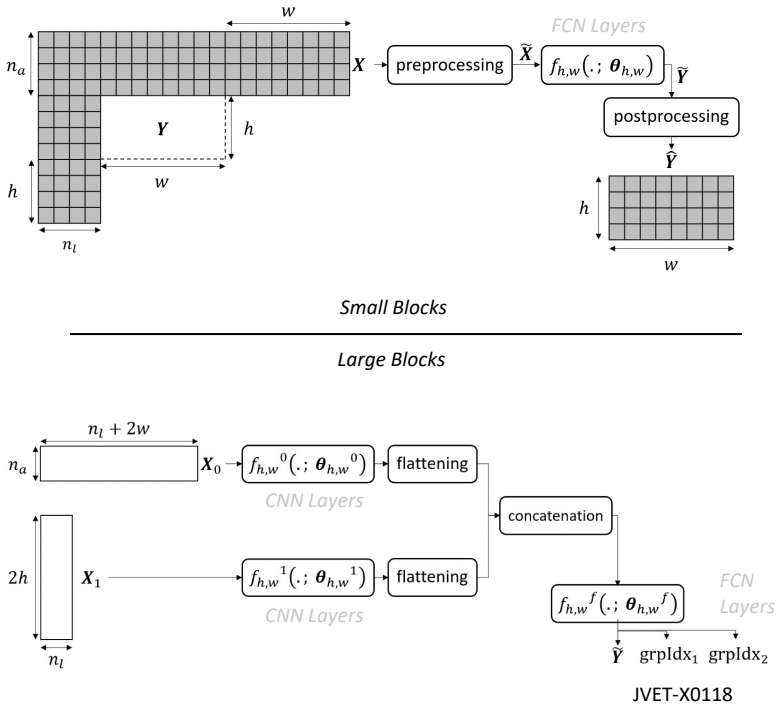




Intra-Prediction

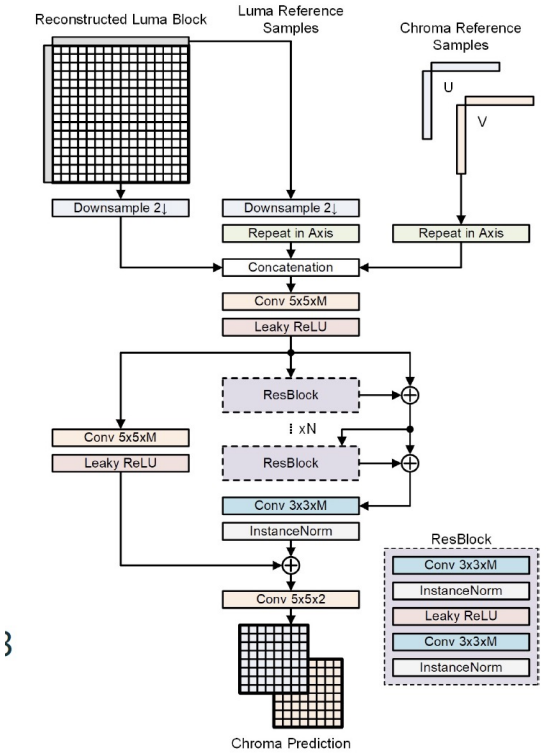
Intra-Prediction

- Intra-Prediction (Example)
  - Predict block Y
  - Small block sizes
    - min(h,w) ≤ 8
    - Three fully connected networks
    - $n_a = n_l = \min(h,w)$
  - Large blocks sizes
    - Convolutional network with six layers
    - $n_a = h/2$; $n_l = w/2$
  - Note: Prediction of grpIdx (used for subsequent VVC processes)
- Recent emphasis has been on reducing complexity



Intra-Prediction

- Additional Aspects
  - Cross-component linear model (CCLM) prediction
    - Goal: Improve/replace existing CCLM mode of VVC
  - Use of Auto-encoders for intra-prediction
    - Feature(s) extracted during encoding stage transmitted to decoder
    - Prediction and residual process replaced by auto-encoder
    - Auto-encoder added as a VVC mode (existing modes remain)



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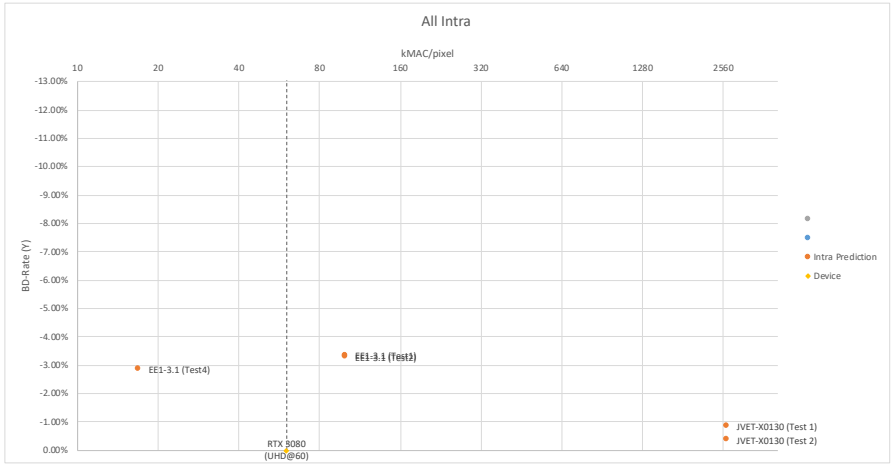
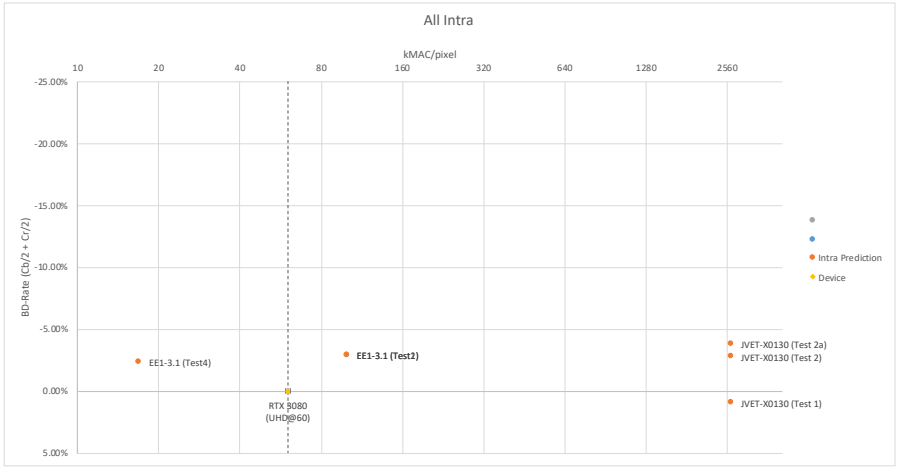
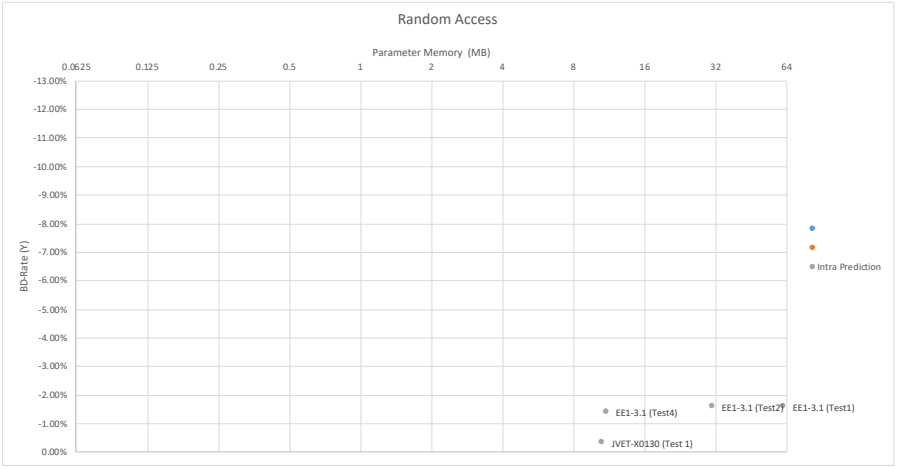
Intra-Prediction





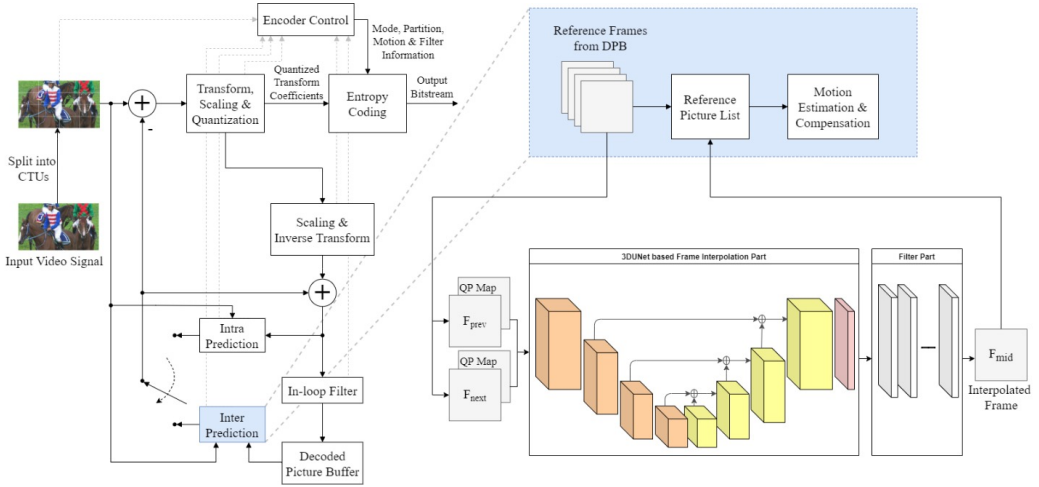
Intra-Prediction



Inter-Prediction

Inter-Prediction

- Virtual reference frames
  - Goal: Use neural network to synthesize a reference frame for prediction
  - Current emphasis
    - Incorporating QP information
    - Reducing complexity
    - Improved training
  - Reported results
    - 1.4k MAC/sample
    - BD-Rate gains: -2.01% (Random Access)



- Other Approaches
  - Use neural networks to filter the motion compensated prediction

JVET-Y0096

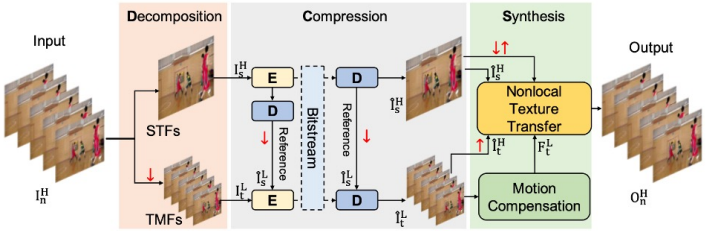
End-to-End

End-to-End

- End-to-end Technologies
  - Small number of proposals on end-to-end video compression
  - General approach
    - Compress intra frames using existing standards
    - Synthesize motion information and texture
      - Informed by low resolution version of motion compensated frame
      - Multi-frame resolution enhancement
      - Multi-frame texture transfer

    or

      - Auto-encoder framework



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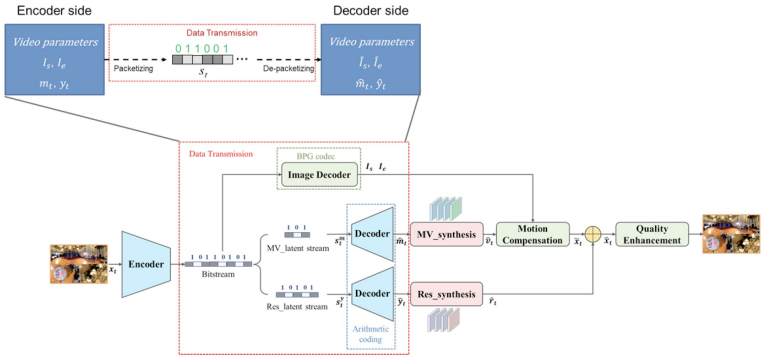
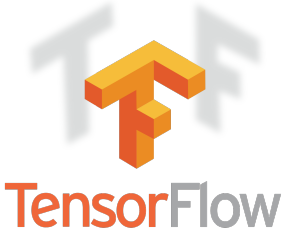


JVET-X0043
(Omnidirectional Video)

NN Environments

Environments

- NN Environments
  - JVET does not have an official development environment
  - Participants commonly use a mixture of TensorFlow and PyTorch
  - JVET is also studying a proposal for a “Small Ad-hoc Deep Learning Library”
    - Asserted to have few dependencies and compatible with BSD-3 licensing clauses
    - Available in JVET-W0181 and JVET-Y0110



Small Ad-hoc Deep Learning Library (SADL)

Language	Pure C++, header only.
Footprint	~3200 LOC, library ~200kB, no dependency
Optimization	Some SIMD at hot spots (best effort)
Compatibility	TF 1.x, 2.x, PyTorch converters
Layer Supports	constants, add, maxPool, matMul, reshape, ReLU,conv2D, mul, concat, max, leakyReLU
Type support	float, int32, int16, int8
Quantization	Support adaptive quantizer per layer

JVET-W0181

Conclusions and Additional Info

Conclusions

- Conclusions
  - Overview of technologies considered in JVET's neural network-based video coding exploration
  - Activity includes enhancement of existing video coding tools, introduction of post-filters, and end-to-end video coding system
  - Significant development in neural network-based filtering
    - In-loop filtering, post-filter, and super-resolution
    - Observed gains of (up to) 13% in random access

Additional Information

- More information
  - All documents available at https://jvet-experts.org/
  - Useful pointers

	21st Meeting	22nd Meeting	23rd Meeting	24th Meeting	25th Meeting
AHG Report	JVET-U0011	JVET-V0011	JVET-W0011	JVET-X0011	JVET-Y0011
Exploration Experiment Report	JVET-U0023	JVET-V0023	JVET-W0023	JVET-X0023	JVET-Y0023
Results Summary	-	-	JVET-W0182	JVET-X0188	JVET-Y0023

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