Adaptive and Scalable Compression of Multispectral Images using VVC

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Outline

- Multispectral image compression
  - Motivation and Goals
- Brief overview of state of the art methods
- Dataset
- Methods
  - "Plain" VVC (used as baseline)
  - PCA VVC
  - Hybrid principle component with least squares (HPCLS)
  - HPCLS-RGB (Scalable approach)
- Conclusions

Multispectral image compression

- Introduction
  - RGB images subdivide the light spectrum into three overlapping bands
    - Undersampling; information loss
  - Multispectral images subdivide the spectrum into more bands
    - Captures more information
  - High spectral resolution results in large data
  - High correlation in spectral dimensions
- Applications:
  - Satellite imaging
  - Space imaging
  - Fraud detection in documents
  - Food processing
  - Biological tissue analysis
  - ...

Goals

- Optimum compression scheme for multispectral imaging
- Incorporate spectral scalability
  - Base layer interpretable by the human visual system
  - Added enhancement layer for full reconstruction
  - Separately decodable
- Study the impact of spectral scalability on compression

State-of-the-art methods for the compression of Multispectral images

- Transform-based compression
  - PCA + 2D DWT[1]
  - Spectral partitioning + PCA + JPEG2000 [2]
  - 3D DWT [3]
  - 3D DCT + SVM [4]
  - HyperLCA transform [5]
- Prediction-based compression combining inter-band and intra-band prediction
  - Adaptive filtering approach [6]
  - Reordering of bands before applying prediction [7], [8], [9]
  - Block-based prediction [10]
  - Super-pixel for prediction [11]
- Network Based approaches
  - Deep Spectral reconstruction [12]

PCA : Principle Component Ananalysis
DWT : Discrete Wavelet Transform
DCT : Discrete Cosine Transform
SVM : Support Vector Machine
HyperLCA : Lossy Compression Algorithm for Hyperspectral Image Systems

Dataset

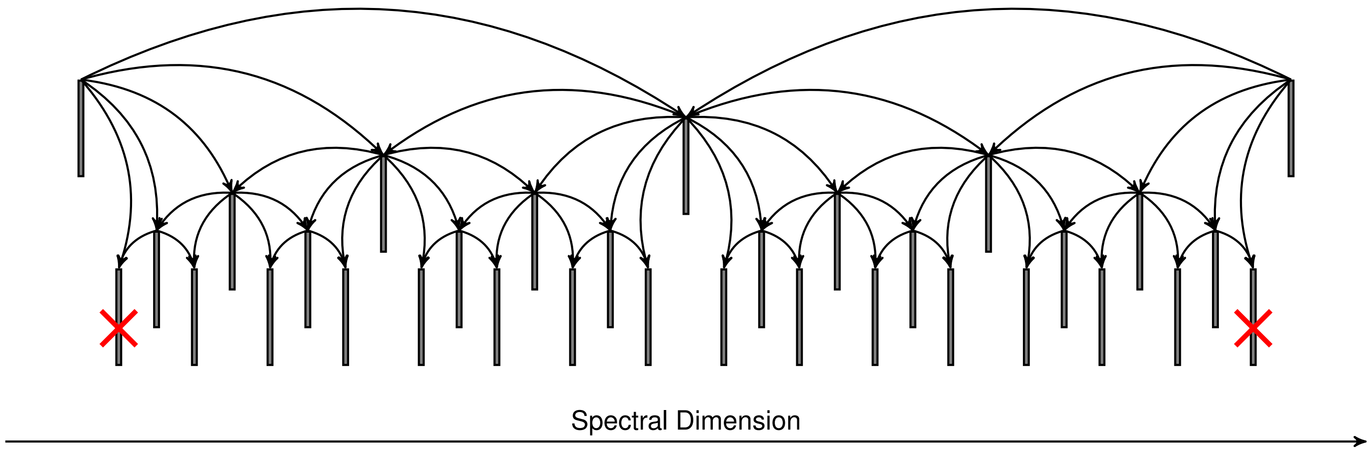
- ARAD HS data set published for NTIRE2020 challenge
- 10 validation images are selected for experiments
- Each image of size 512×482 is cropped into 256×256, resulting in 40 images
- Each MSI has 31 bands
- Sampled at 10nm increments in 400-700 nm range

Example images from ARAD HS data set [13]

Methods

- The following methods are analyzed in a test environment for initial experiments
  - 3D-DCT, PCA-DCT, Auto-encoder, Hybrid Least Squares Predictor (HLS), Hybrid Principle Component Least Squares Predictor (HPCLS)
- The following novel methods are implemented using VVC reference software [14]
  - Plain VVC
  - PCA-VVC
  - HPCLS
  - HPCLS-RGB (Scalable approach)
- The algorithms are evaluated using PSNR and compressed file size measured in bits
- The results are averaged over all the images

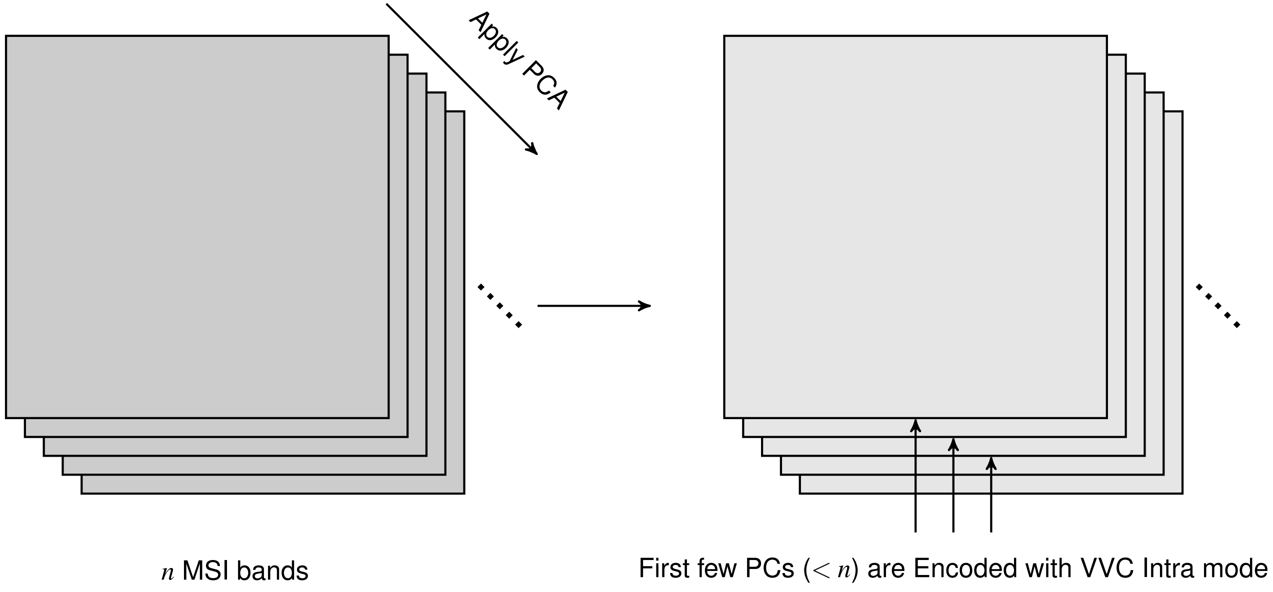
Plain VVC



Multispectral images are encoded using VVC reference software (VTM 15.0)

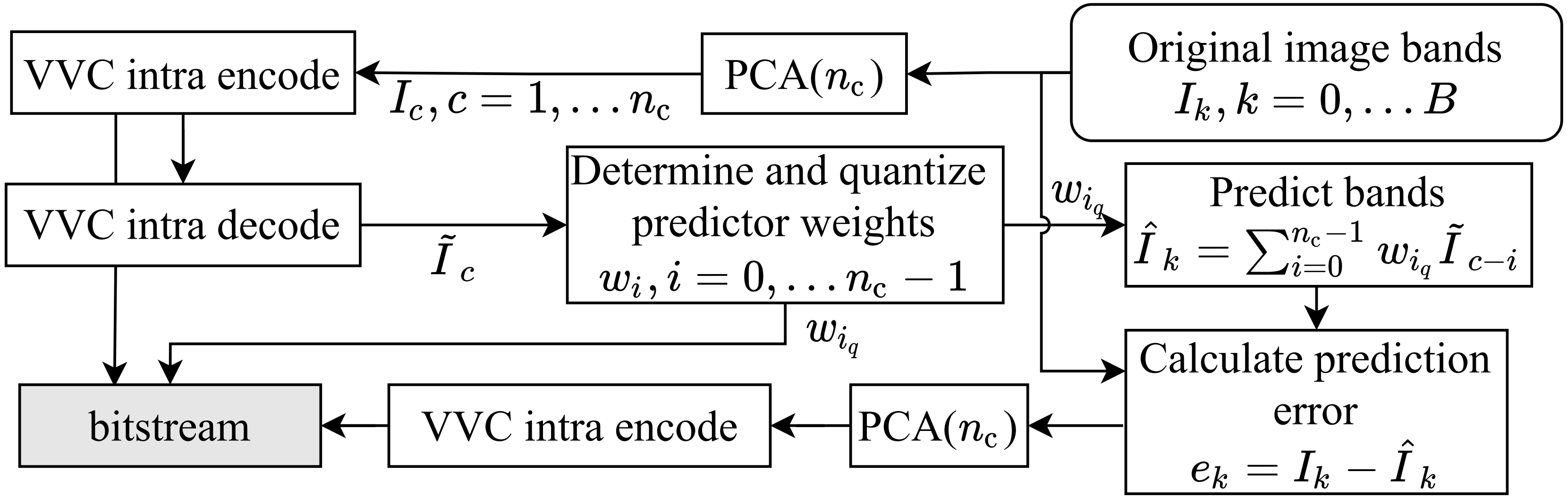
- Temporal prediction concepts are applied to spectral decorrelation.
- Default random access configuration with GOP-32 is modified to be used.
- Bands are kept in sequential order.
- Apart from key pictures, all other bands are encoded with the same QP, key pictures with a QP offset of -3.
- QP is chosen from [5,50] with a step size of 5.

PCA VVC



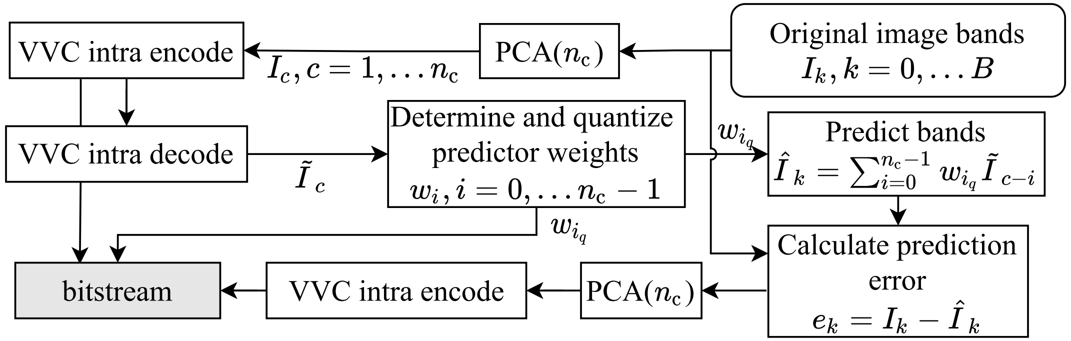
- PCA is applied for spectral decorrelation.
- Only the first few principle component images are transmitted.
- Number of tested principle components to be transmitted in error images $n_c \in [1, 10]$.
- PCA basis vectors are quantized with $\Delta_v = 2^{-13}$ and transmitted.
- VVC intra mode is used for spatial decorrelation.

HPCLS - Hybrid principle component with least squares

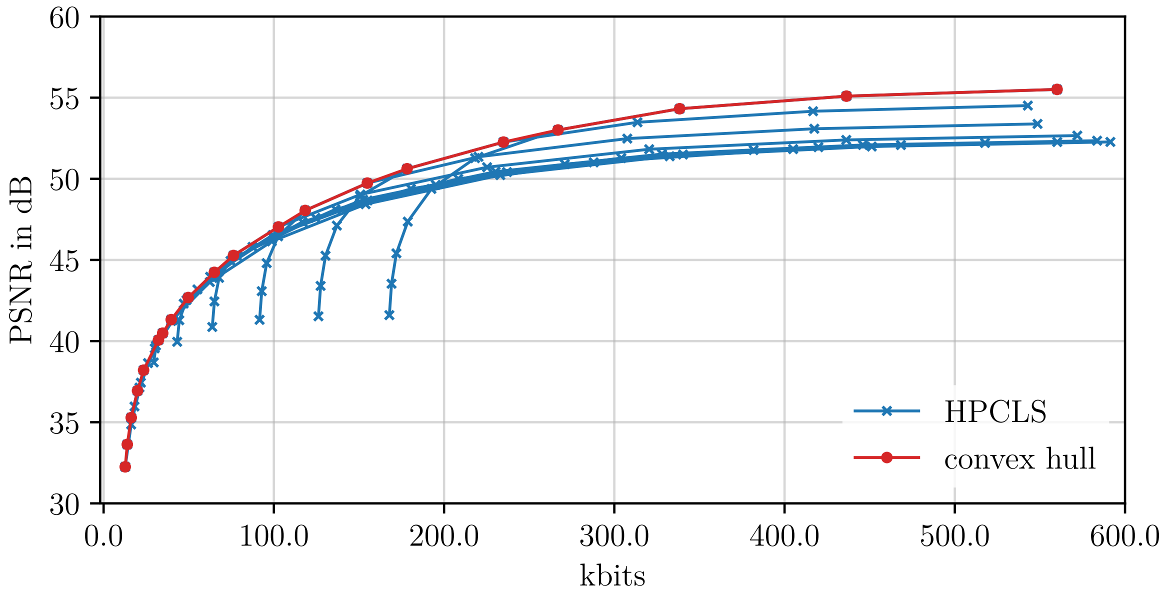


HPCLS - Hybrid principle component with least squares

- A test environment where VVC was replaced by DCT, is used to narrow down parameter search
- The following subset of parameters are tested using VVC
  - Number of reference bands for prediction $n_{\text{ref}} \in \{1, 2, 3\}$
  - QP for reference bands $q_{\text{ref}} \in [5, 50]$.
  - Number of principle components in error images $n_c \in [1, 6]$
  - Block size $S_p = 64$
  - PCA basis vectors are quantized with $\Delta_v = 2^{-13}$ and transmitted.
  - Predictor weights are quantized with $\Delta_w = 2^{-12}$ and transmitted.

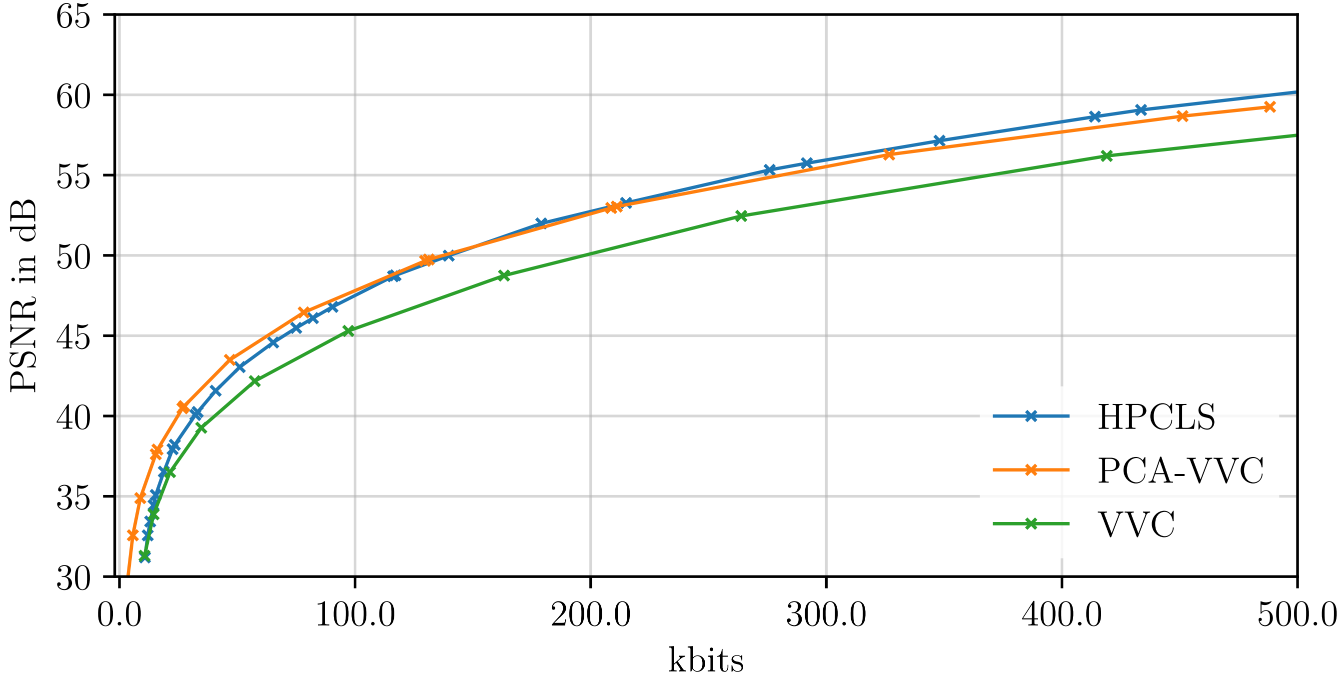


HPCLS parameter setting



- HPCLS for varying q_{ref} with $n_{\mathrm{ref}}{=}1$ and $n_{\mathrm{c}}{=}3$ fixed.
- Lower q_{ref} shifts the RD curve towards the to right.
- The convex hull is established by the best-performing rate points.
- This parameter setting is used for further comparison.

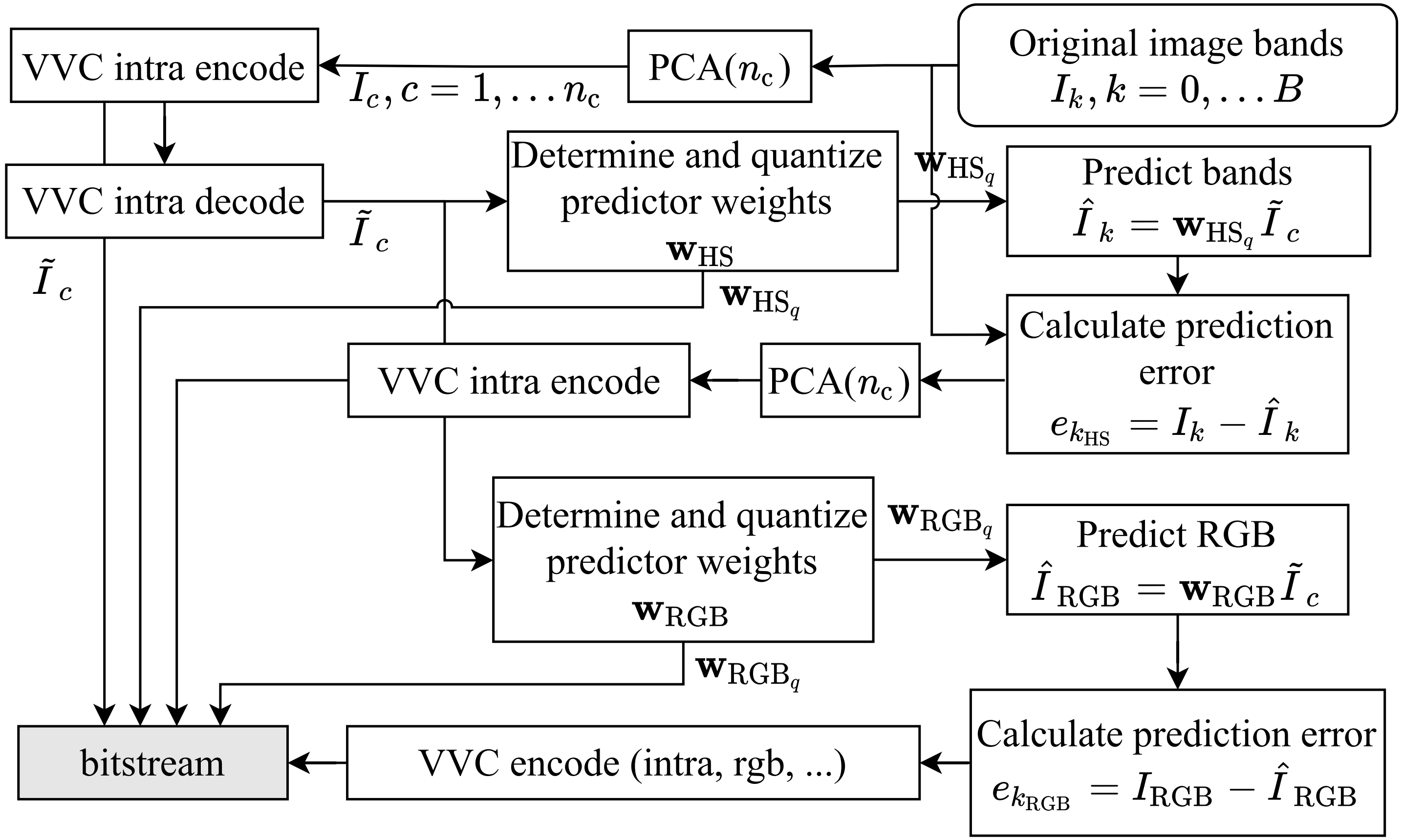
Comparisn of HPCLS, PCA-VVC and "plain" VVC



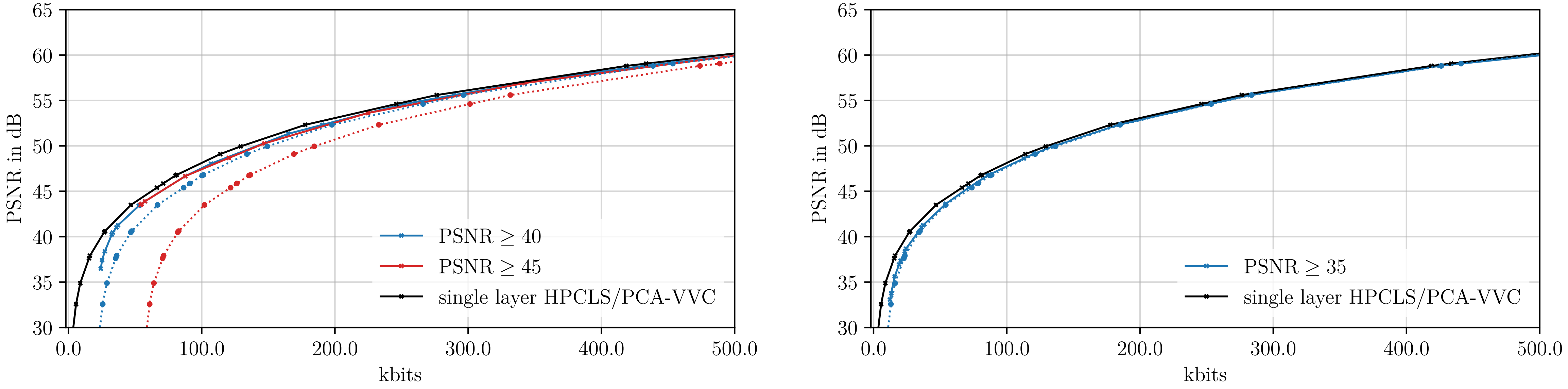
The convex hull RD curves for PCA-VVC and HPCLS is compared against "plain" VVC.

HPCLS-RGB (scalable approach)

- Parameter setting for convex hull is used as HPCLS.
- Additionally varying QP to encode residuals for RGB images.
- This technique is compared with "simulcast" which is a technique to add an RGB preview to compressed non-scalable approach.



HPCLS-RGB vs simulcast



Comparison of simulcast HPCLS/PCA-VVC (dotted) and HPCLS-RGB (solid) using adaptive and scalable coding structures for three different qualities of the RGB preview (35, 40 and 45 dB PSNR), plotted against single layer HPCLS/PCA-VVC, which does not provide a preview.

Summary and Conclusions

- Summary
  - State of the art methods to compress multispectral images
  - Description and comparison of "Plain" VVC, PCA-VVC, HPCLS
  - Description of the novel scalable approach HPCLS-RGB
  - Comparison of HPCLS-RGB against the simulcast method (best RD points combining HPCLS and PCA-VVC)
- Conclusions
  - For high RGB reconstruction quality and low MSI reconstruction quality, HPCLS-RGB outperforms the simulcast significantly
  - The non-scalable HPCLS outperforms PCA-VVC for reconstruction quality above 51db
  - A superior entropy coding scheme for the predictor weights might be helpful

Literature I

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