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► **To cite this version:**

Thierry Dumas, Franck Galpin, Philippe Bordes. Iterative training of neural networks for intra prediction. 2020. hal-02494047

**HAL Id: hal-02494047**

**<https://hal.science/hal-02494047>**

Preprint submitted on 2 Mar 2020

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# Iterative training of neural networks for intra prediction

Thierry Dumas, Franck Galpin, and Philippe Bordes

**Abstract**— This paper presents an iterative training of neural networks for intra prediction in a block-based image and video codec. First, the neural networks are trained on blocks arising from the codec partitioning of images, each paired with its context. Then, iteratively, blocks are collected from the partitioning of images via the codec including the neural networks trained at the previous iteration, each paired with its context, and the neural networks are retrained on the new pairs. Thanks to this training, the neural networks can learn intra prediction functions that both stand out from those already in the initial codec and boost the codec in terms of rate-distortion. Moreover, the iterative process allows the design of training data cleansings essential for the neural network training. When the iteratively trained neural networks are put into H.265 (HM-16.15),  $-4.2\%$  of mean dB-rate reduction is obtained, that is  $-1.8\%$  above the state-of-the-art. By moving them into H.266 (VTM-5.0), the mean dB-rate reduction reaches  $-1.9\%$ .

**Index Terms**—Intra prediction, neural networks, image partitioning.

## I. INTRODUCTION

**T**HE prediction of an image region from a set of pixels around this region, referred to as “context”, applies to computational photography and image editing [1], [2], where it is known as “inpainting”, and video compression [3], where it is called “intra prediction”.

The prediction of an image block from its context via a machine learning approach is made difficult by the multimodal nature of the distribution  $p(\mathbb{Y}|\mathbb{X})$  of the random vector block  $\mathbb{Y}$  given the random vector context  $\mathbb{X}$ . For instance, let us say that a neural network is designed to predict a block from its context, and its training consists in minimizing over its parameters the l2-norm of the difference between a training block and its neural network prediction, averaged over a training set of pairs of a block and its context sampled from  $p(\mathbb{X}, \mathbb{Y})$ . The training assumes that  $p(\mathbb{Y}|\mathbb{X})$  is Gaussian with mean the neural network prediction. Besides, the training amounts to the maximum likelihood estimation of this mean [4]. After the training, as the prediction is the sample mean of the multimodal distribution, it looks blurry [5].

This is commonly resolved by adversarial training [6], which causes the learned model to pick a mode of  $p(\mathbb{Y}|\mathbb{X})$ . For inpainting, this solution is suitable as a prediction needs to be sharp and consistent with the context [7], [8], [9].

However, for intra prediction, adversarial training is not appropriate. Indeed, a neural network trained in an adversarial

way infers a likely prediction of a block but with potentially large pixelwise differences with it [10], [11].

Instead, one can consider a class  $\mathcal{C}$  of pairs of a block and its context defined by a known context-block relationship, then train a neural network on samples from  $\mathcal{C}$ , hence limiting the blurriness of the neural network predictions for  $\mathcal{C}$ . For example, in [12],  $\mathcal{C}$  gathers the blocks provided by the H.265 partitioning [13] of images, each paired with its context. The context-block relationship is that a block of  $\mathcal{C}$  is relatively well predicted from its reference samples by the H.265 intra prediction [14], see Figures 1 and 2, because the H.265 intra prediction drives the partitioning [15]. But, this has two drawbacks. Firstly, the neural network learns mainly the H.265 linear intra prediction. Secondly, the training set contains some pairs of a block and its context with discontinuities between the spatial distribution of pixel intensities in the block and that in its context, for which no prediction of good quality can be learned, thus hampering the training. For instance, in Figure 1, the above-mentioned discontinuities are illustrated by the diagonal dark gray border in the context not extending into the block. A neural network cannot infer this from the context **alone**, see the neural network prediction in Figure 1. Likewise, in Figure 2, the above-mentioned discontinuities are represented by the horizontal border in the context tilting downward while extending into the block, instead of extending horizontally. Again, a neural network cannot infer this from the context **alone**, see Figure 2. In contrast, during the H.265 partitioning, these discontinuities are not problematic as the encoder considers **both** this block **and** its reference samples to select the best H.265 mode in terms of rate-distortion.

To address the two drawbacks, an iterative training of neural networks for intra prediction in a block-based image and video codec is proposed. At the first iteration, a set of neural networks is trained on samples from a class  $\mathcal{C}$  similar to that in [12] and put into the codec as a single additional intra prediction mode. During each successive iteration,  $\mathcal{C}$  now gathers the blocks given by the image partitioning of the codec including this single additional mode, each paired with its context, and the set of neural networks is retrained on samples from  $\mathcal{C}$ . This way, the neural networks can learn an intra prediction progressively deviating from that in the initial codec while being beneficial in terms of rate-distortion. Moreover, from the second iteration, the pairs of a block and its context with the above-mentioned discontinuities can be detected by comparing the quality of the neural network prediction against that of the initial codec and left out of the training set.

The set of neural networks in [16] is trained iteratively with H.265 as codec, then inserted into H.265 as a single

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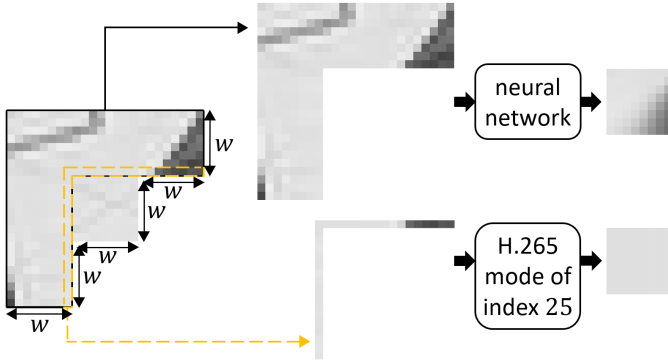


Fig. 1: Prediction of a  $w \times w$  luminance block returned by the H.265 (HM-16.15) partitioning of the first frame of “BQSquare” in 4:2:0 with Quantization Parameter (QP) of 22. At the top, a neural network trained as in [12] predicts this block from its context of decoded pixels. At the bottom, the H.265 mode of index 25 selected during the partitioning predicts this block from its decoded reference samples, which are made of a row of  $2w + 1$  decoded pixels above this block and a column of  $2w$  decoded pixels on its left side.  $w = 8$ . The prediction PSNRs of the neural network and the H.265 mode of index 25 are 15.82 dB and 35.46 dB respectively.

additional intra prediction mode, leading to  $-4.2\%$  of mean dB-rate reduction. This improves on the state-of-the-art [12], [17] by  $-1.8\%$ . When the trained neural networks are put into H.266 as a single additional mode, the mean dB-rate reduction is  $-1.9\%$ .

The contributions in this paper can be summed up as:

- We propose an iterative training of neural networks for intra prediction.
- A generic preprocessing of the context of a block and a generic postprocessing step are formulated to fit various block-based codecs, e.g. H.265 and H.266.
- A signalling of the single additional neural network-based intra prediction mode in H.266 is introduced.

## II. PROPOSED ITERATIVE TRAINING OF NEURAL NETWORKS FOR INTRA PREDICTION

The proposed approach aims at training a set of neural networks, which becomes a single additional intra prediction mode in a block-based codec. Given that a neural network for intra prediction maps the L-shape context of a rectangular block to the predicted block, see Figure 1 and 2, fully-convolutional architectures [18] can hardly do this mapping. The L-shape will be clarified in Section II-C. As full-connections are part of the architecture, the number of neural network parameters depends on the block size. Therefore, blocks of each possible size are predicted by a different neural network. If a block to be predicted in the codec can be of size  $w \times h$ ,  $(h, w) \in Q$ ,  $Q$  denoting the set of possible pairs of block height and width in the codec, the set of neural networks comprises  $\text{card}(Q)$  neural networks.

Section II-A explains the iterative aspect of the training. Then, Sections II-B to II-E justify its features. Finally, Sections II-F and II-G highlight the separate benefits of the two key

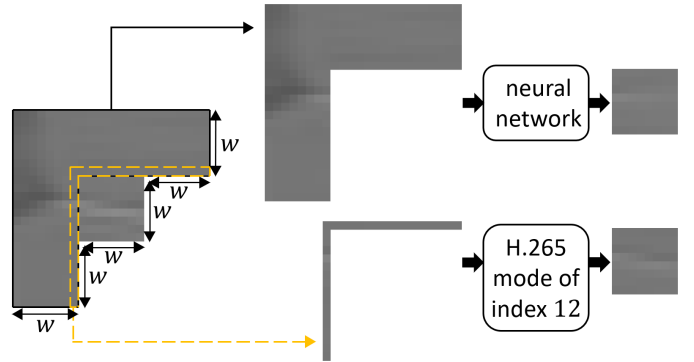


Fig. 2: Prediction of a  $w \times w$  luminance block returned by the H.265 (HM-16.15) partitioning of the first frame of “BasketballPass” in 4:2:0 with QP = 22. At the top, a neural network trained as in [12] predicts this block from its context of decoded pixels. At the bottom, the H.265 intra prediction mode of index 12 selected during the partitioning predicts this block from its decoded reference samples.  $w = 8$ . The prediction PSNRs of the neural network and the H.265 mode of index 12 are 31.90 dB and 37.04 dB respectively.

features in terms of rate-distortion. The precise details of the iterative training are specified when either H.265 or H.266 is chosen as codec because they stand out as two of the most advanced video compression standards [19].

### A. Modification of the training data over iterations

The first thrust of our approach is to avoid the case where a learned model gives blurry predictions because it was trained on an unrestricted variety of pairs of a block and its context in which many predictions of a block are likely given its context, cf. the multimodality discussed in Section I. That is why, first, a set  $\Gamma$  of 8-bit  $YCbCr$  images is encoded via the codec to yield the training sets  $\{S_{h,w}\}_{(h,w) \in R}$ , where  $S_{h,w}$  contains pairs of a luminance block of size  $w \times h$  provided by the partitioning of an image of  $\Gamma$  and its context. The use of  $R \subseteq Q$  instead of  $Q$  will be explained two paragraphs later. Then, each neural network  $f_{h,w}(\cdot; \theta_{h,w})$ , parametrized by  $\theta_{h,w}$ , is trained on  $S_{h,w}$ , see the first loop of Algorithm 1.

At this stage of the training, the learned models tend to reproduce the codec intra prediction [12]. This results from the combination of two factors. Firstly, the context fed into a neural network always includes the reference samples fed into the codec intra prediction [12], [16], [17], [20], [21], see Figures 1 and 2, implying that this neural network can learn the codec intra prediction. Secondly, the partitioning mechanism generating the training blocks ensures that each training block is “well” predicted from its reference samples by the codec intra prediction [15], meaning that the codec intra prediction is a “good” solution to the learning problem for most of the training pairs. To allow the neural networks to learn an intra prediction progressively diverging from that in the codec while being valuable in terms of rate-distortion, for  $l - 1$  iterations, (i) training sets are built as described above, but replacing the codec by the codec with the single additional neural network-based mode, (ii) the neural networks are retrained on the new training sets, see the second loop of Algorithm 1.

---

**Algorithm 1** : iterative training.

“getPartition”, “getPartitionNN”, and  $\mathcal{L}_{h,w}$  are defined by Algorithm 2, Algorithm 3, and (1) respectively.

Inputs:  $\Gamma$  and  $l \in \mathbb{N}^*$

```

{Sh,w}(h,w)∈R = getPartition (Γ)
for all (h, w) ∈ R do
  θh,w(0) = minθh,w ℒh,w (Sh,w; θh,w) where θh,w is
  randomly initialized.
end for
for all i ∈ [|1, l - 1|] do
  {Sh,w}(h,w)∈R = getPartitionNN (Γ; {θh,w(i-1)}(h,w)∈R)
  for all (h, w) ∈ R do
    θh,w(i) = minθh,w ℒh,w (Sh,w; θh,w) where θh,w =
    θh,w(i-1) at initialization.
  end for
end for
Output: {θh,w(l-1)}(h,w)∈R

```

---

A neural network may be needed to predict blocks of a given size in the codec but cannot be trained via Algorithm 1. This occurs when this block size exists in the intermediate steps of the image partitioning, not at the output of the partitioning. For instance, a luminance Prediction Block (PB) in an intermediate step of the H.265 partitioning can be of size either  $4 \times 4$ ,  $8 \times 8$ ,  $16 \times 16$ ,  $32 \times 32$  or  $64 \times 64$ . Therefore,  $Q = \{(4, 4), (8, 8), (16, 16), (32, 32), (64, 64)\}$ . However, the H.265 partitioning returns luminance Transform Blocks (TBs) of sizes  $4 \times 4$ ,  $8 \times 8$ ,  $16 \times 16$ , and  $32 \times 32$  exclusively, cf. Section 3.2.4.1 of [22]. Thus,  $R = \{(4, 4), (8, 8), (16, 16), (32, 32)\}$ . In this case, each neural network predicting blocks of size  $w \times h$ ,  $(h, w) \in Q - R$ , is trained by following [16].

### B. Generic intra prediction with respect to block textures

The single additional neural network-based mode should predict any texture found in the blocks of the image partitioning. This implies that the training sets must span the variety of textures in these blocks. But, large blocks from the partitioning are usually smooth whereas small blocks exhibit unsmooth textures [23], [24], especially at small Quantization Parameters (QPs). To maintain some texture diversity in each training set, the QP for encoding each image in  $\Gamma$  is uniformly drawn from a set unbalanced towards large QPs, see Algorithms 2 and 3.

### C. Intra prediction from a context with missing information

In a block-based codec, the shape of the context of a block is constrained. For instance, in H.265 and H.266, as the blocks are processed in raster-scan order combined with Z-scan order, c.f. Sections 3.2.2 to 3.2.4 of [22] and [25], the context can only include decoded pixels located above and on the left side of this block. To comply with the constraints, the context  $\mathbf{X}$  takes from now on a generalized version of the context shape introduced in [16] for H.265, see Figure 3. It comprises  $n_l$

---

**Algorithm 2** : getPartition.

“extractPair” is detailed in Figure 4. “codec” denotes the codec of interest. “break” breaks out of the innermost enclosing “for” loop.

Input:  $\Gamma$

```

for all (h, w) ∈ R do
  Sh,w = {}
end for
for all I ∈ Γ do
  QP ~ U {22, 27, 32, 37, 42}
  Î, B = codec (I, QP)
  shuffle (B)
  i = 0
  for all (x, y, h, w, n0, n1) ∈ B do
    Xc, Yc = extractPair (Î, Î, x, y, h, w, n0, n1)
    Sh,w.append ((Xc, Yc))
    i += 1
    if i == 20 then
      break
    end if
  end for
end for
Output: {Sh,w}(h,w)∈R

```

---



---

**Algorithm 3** : getPartitionNN

“extractPair” is explained in Figure 4. “codecNN” denotes the codec with the single additional neural network-based intra prediction mode.

Inputs:  $\Gamma$  and {θ<sub>h,w</sub>}<sub>(h,w)∈R</sub>

```

for all (h, w) ∈ R do
  Sh,w = {}
end for
for all I ∈ Γ do
  QP ~ U {22, 27, 32, 37, 42}
  Î, B = codecNN (I, QP; {θh,w}(h,w)∈R)
  shuffle (B)
  i = 0
  for all (x, y, h, w, n0, n1, s, dnn, dc, isSplitTBs) ∈ B do
    if isSplitTBs or max (h, w) ≤ 4 then
      isAdded = s == snn
    else
      isAdded = dnn ≤ γdc
    end if
    if isAdded then
      Xc, Yc = extractPair (Î, Î, x, y, h, w, n0, n1)
      Sh,w.append ((Xc, Yc))
      i += 1
    end if
    if i == 20 then
      break
    end if
  end for
end for
Output: {Sh,w}(h,w)∈R

```

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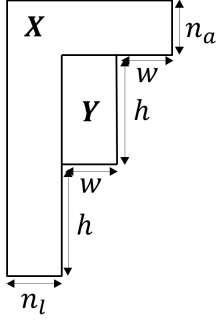


Fig. 3: Positions of a  $w \times h$  block  $\mathbf{Y}$  and its context  $\mathbf{X}$ .

columns of  $2h$  decoded pixels on the left side of the block  $\mathbf{Y}$  and  $n_a$  rows of  $n_l + 2w$  decoded pixels above the block. As long-range spatial dependencies between decoded pixels above and on the left side of the block are needed for prediction only in the case of a large block to be predicted, a rule for defining  $n_l$  and  $n_a$  consists of making the ratio  $\delta$  between the size of the context and that of the block constant [16]. To keep a constant term in this ratio whatever  $h$  and  $w$  while limiting the context size,  $n_a = n_l = \min(h, w)$ . Then,

$$\delta = \min(h, w) \left( \frac{\min(h, w)}{hw} + \frac{2}{h} + \frac{2}{w} \right).$$

More importantly, the block-based processing also causes information to be missing in the context of a block. Indeed, the  $n_0 \in [0, h]$  bottommost rows and/or the  $n_1 \in [0, w]$  rightmost columns of pixels in the context may not be decoded yet, depending on the position of this block in its macro block, called Coding Tree Block (CTB) in H.265 and H.266 [14].

To overcome this, the authors in [17] first design several contexts per block size, each context containing available decoded pixels exclusively. Then, one neural network is trained per context. During the test phase, depending on the availability of the decoded pixels around a block of a given size, the context is chosen, and its associated neural network is used for prediction. But, this increases the number of neural networks in the codec, i.e. the memory cost of their parameters.

Differently, in [16], a single context is created per block size, and the missing decoded pixels are masked with the mean pixel intensity over training luminance images. Unfortunately, the mask value belongs to the range of the available decoded pixel values, leading to ambiguities between the masked portions of the context and its unmasked portions for the neural network fed with the context.

Instead, to take the mask value out of this range, the missing decoded pixels in  $\mathbf{X}$  are first covered by a mask of value 255, see the step called “mask” in Figure 4. Then, the mean  $\mu$  of the available decoded pixels is subtracted from them, yielding the preprocessed context  $\mathbf{X}_c$ . Moreover,  $\mu$  is subtracted from the block  $\mathbf{Y}$ , giving rise to the preprocessed block  $\mathbf{Y}_c$ , see the step called “center” in Figure 4.

Now that a training pair  $(\mathbf{X}_c, \mathbf{Y}_c)$  is defined, our iterative training can be further specified. In Algorithm 2, the encoding of an image  $\mathbf{I}$  of  $\Gamma$  via the codec returns a reconstruction  $\hat{\mathbf{I}}$  of  $\mathbf{I}$  and a set  $B$  of characteristics of each luminance block from the image partitioning. Then, for some of these luminance blocks,

the block characteristics enable to create a training pair of a preprocessed block and its preprocessed context, see Figure 4. The same description goes for Algorithm 3, except that the codec is replaced by the codec with the single additional neural network-based mode.

#### D. Balancing the contributions of images to the training data

If the set  $\Gamma$  contains  $\text{YCbCr}$  images of various sizes and, for each of them, the characteristics of each luminance block from the image partitioning give rise to a different training pair, the textures of the large images are more heavily represented in the training sets  $\{S_{h,w}\}_{(h,w) \in R}$  than those of the small images. For instance, let us focus on  $S_{16,8}$ . The partitioning of the  $1600 \times 1200$  image in Figure 5 returns  $1379 \ 8 \times 16$  luminance blocks whereas that of the  $480 \times 360$  image gives  $158 \ 8 \times 16$  luminance blocks. This means that almost 9 times more training pairs in  $S_{16,8}$  come from the  $1600 \times 1200$  image. To avoid this, the number of pairs of a preprocessed block and its preprocessed context generated by the partitioning of an image of  $\Gamma$  is limited to 20, see Algorithms 2 and 3.

Still in order to build training sets with diverse textures, for each large image in  $\Gamma$ , the training set  $S_{h,w}$  should not be filled with the first 20  $w \times h$  preprocessed blocks coming from the top-left of this image, each paired with its preprocessed context. Thus,  $B$  is shuffled before picking from it block characteristics to create training pairs, see Algorithms 2 and 3.

#### E. Ignoring each training block viewed as unpredictable from its context alone

For some blocks given by the partitioning of images, the prediction of the block from its context alone via a neural network can be viewed as unfeasible, see Figures 1 and 2. If a neural network is trained on these blocks, each paired with its context, it learns to provide blurry predictions. To resolve this, these pairs must be identified and removed from the training sets. But, the identification is challenging.

A solution is to first choose a reference intra predictor that selects its prediction of a block based on **both** this block **and** some neighboring decoded pixels. Then, a given block is labeled as unpredictable from its context **alone** via a pretrained neural network if this neural network infers from the context a prediction of low quality relatively to the prediction of the reference intra predictor. The H.265 intra prediction and that in H.266 appear to be suitable reference intra predictors as the intra prediction mode for predicting a given block is selected on the encoder side by considering both this block and its reference samples. Based on this, the following basic criterion is derived. For a  $w \times h$  luminance TB provided by the partitioning of an image of  $\Gamma$ , if the mean-squared error  $d_{nn} \in \mathbb{R}_+^*$  between the luminance TB and its neural network prediction is strictly larger than  $\gamma d_c$ ,  $d_c \in \mathbb{R}_+^*$  denoting the third lowest mean-squared error between the luminance TB and the mode prediction over all the regular codec modes, this TB is not added to the training set  $S_{h,w}$ . By searching for the value of  $\gamma \in \{0.5, 1.05, 1.55\}$  yielding the best rate-distortion performance in Section II-F3,  $\gamma = 1.05$  was obtained.

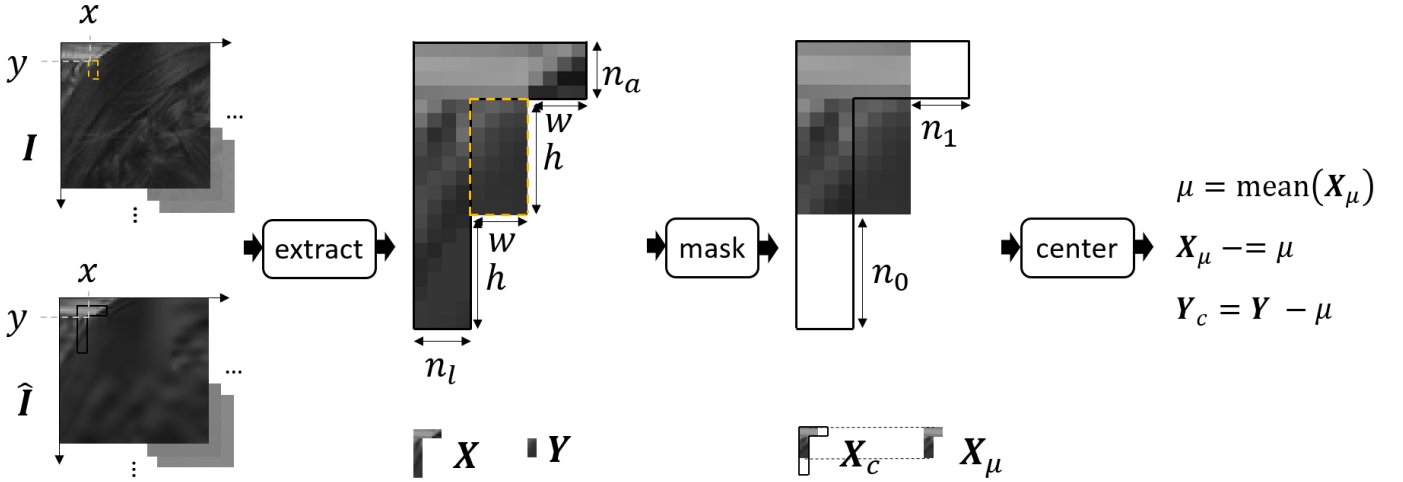


Fig. 4: Creation via “extractPair” of a pair of a  $w \times h$  preprocessed luminance block  $Y_c$  and its preprocessed context  $X_c$ . “extractPair” gathers “extract”, “mask”, and “center”.  $Y$  is extracted from the luminance channel of the first frame  $I$  of “BlowingBubbles” in 4:2:0 while  $X$  is extracted from the luminance channel of its reconstruction  $\hat{I}$  via H.266 (VTM-5.0) with QP = 37. The coordinates of the pixel at the top-left of  $Y$  in  $I$  are  $x = 12$  and  $y = 8$ .  $h = 8$ ,  $w = 4$ ,  $n_0 = 8$ , and  $n_1 = 4$ .

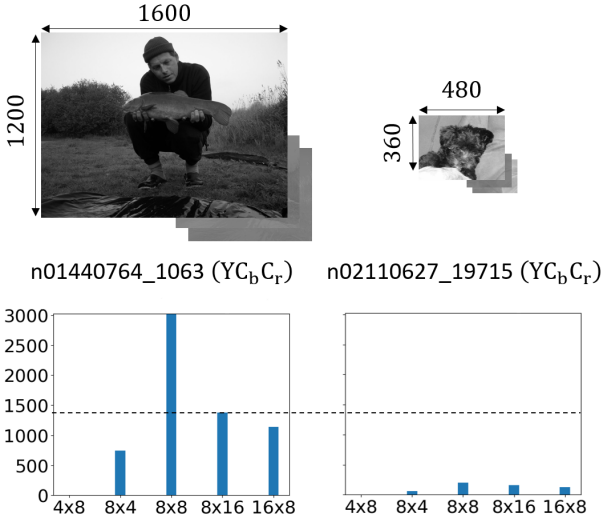


Fig. 5: Number of luminance blocks of sizes  $4 \times 8$ ,  $8 \times 4$ ,  $8 \times 8$ ,  $8 \times 16$ , and  $16 \times 8$  returned by the partitionings of “n01440764\_1063” and “n02110627\_19715” in the ILSVRC2012 training RGB images [26], converted into  $YCbCr$  and 4:2:0, via H.266 (VTM-5.0) with QP = 32.

However, the basic criterion has two downsides. Firstly, for a given luminance TB returned by the partitioning of an image, the computation of  $d_{nn}$  and  $d_c$  inside the codec increases significantly the encoding time if this TB arises from the split of its parent PB into multiple TBs. Indeed, as the intra prediction mode is defined at the PB level, the (either H.265 or H.266) encoder runs the prediction of each intra prediction mode on a given luminance PB to compare them<sup>1</sup>. This implies that, if this PB is not split into multiple TBs, there is no need

to run additional predictions for calculating  $d_{nn}$  and  $d_c$  for the TB equivalent to its parent PB. In contrast, when a luminance PB is split into multiple TBs, the encoder does not run the prediction of each mode on a child TB as each TB inherits its mode from its parent PB<sup>2</sup>. In this case, the computation of  $d_{nn}$  and  $d_c$  for a child TB requires additional predictions.

To remedy to the first downside, if the luminance TB results from the split of its parent PB into multiple TBs, the basic criterion is replaced by another criterion that involves neither  $d_{nn}$  nor  $d_c$ . More precisely, for a  $w \times h$  luminance TB given by the partitioning of an image of  $\Gamma$ , if the luminance TB is equivalent to its parent PB, i.e. its flag “isSplitTBs” is false, the basic criterion applies. Otherwise, the alternative criterion is that if the index  $s$  of the intra prediction mode of the luminance TB is equal to the index  $s_{nn}$  of the single additional neural network-based mode, this TB is added to the training set  $S_{h,w}$ .

As a second shortcoming, the basic criterion involves prediction PSNRs exclusively, which incurs an adverse effect for very small luminance TBs. Indeed, when several intra prediction modes yield predictions of a luminance PB with comparable qualities, the selection of the mode for predicting this PB and its child TB(s) depends on the signalling cost of each mode. This dependency increases as this PB and its child TB(s) get smaller because the first cost involved in the selection linearly combines a distortion term and a signalling term, the former growing with the block size, unlike the latter [27], [28], [29]. As the basic criterion does not consider these signalling costs, there exist discrepancies between the small blocks in the training sets and those in the codec for which the single additional neural network-based mode is likely to be selected.

<sup>1</sup>For H.265, see “TEncSearch::estIntraPredLumaQT” at <https://hevc.hhi.fraunhofer.de/trac/hevc/browser/trunk/source/Lib/TLibEncoder/TEncSearch.cpp>. For H.266, see “IntraSearch::estIntraPredLumaQT” at [https://vcgit.hhi.fraunhofer.de/jvet/VVCSoftware\\_VTM/blob/master/source/Lib/EncoderLib/IntraSearch.cpp](https://vcgit.hhi.fraunhofer.de/jvet/VVCSoftware_VTM/blob/master/source/Lib/EncoderLib/IntraSearch.cpp)

<sup>2</sup>For H.265, see “TEncSearch::TEncSearch::xRecurIntraCodingLumaQT” at <https://hevc.hhi.fraunhofer.de/trac/hevc/browser/trunk/source/Lib/TLibEncoder/TEncSearch.cpp>. For H.266, see “IntraSearch::IntraSearch::xRecurIntraCodingLumaQT” at [https://vcgit.hhi.fraunhofer.de/jvet/VVCSoftware\\_VTM/blob/master/source/Lib/EncoderLib/IntraSearch.cpp](https://vcgit.hhi.fraunhofer.de/jvet/VVCSoftware_VTM/blob/master/source/Lib/EncoderLib/IntraSearch.cpp)



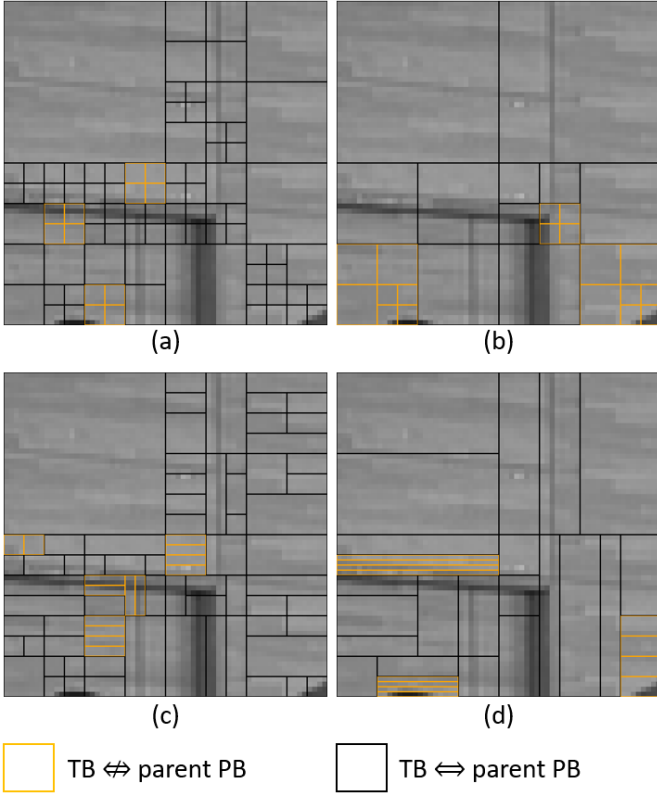


Fig. 6: Partitioning of the first  $64 \times 64$  block of the luminance channel of the first frame of “BasketballPass” in 4:2:0 via H.265 (HM-16.15) with (a) QP = 22 and (b) QP = 37 and H.266 (VTM-5.0) with (c) QP = 22 and (d) QP = 37.

Unfortunately, the solution to the first downside does not tackle the second one. Indeed, although the alternative criterion takes into account the signalling cost of each intra prediction mode, the condition on “isSplitTBs” does not guarantee that the alternative criterion systematically applies to small luminance TBs. For instance, the pieces of the partitionings of the image luminance channel displayed in Figure 6 via H.265 and H.266 yield many relatively small TBs that are equivalent to their parent PB, i.e. “isSplitTBs” is false. In order to apply the alternative criterion to all relatively small luminance TBs, the condition for picking it over the basic criterion becomes “isSplitTBs or  $\max(h, w) \leq 4$ ”, see Algorithm 3.

#### F. Benefits of the two key features in terms of rate-distortion

Now that the proposed iterative training is fully detailed, the benefits of its two key features, namely its iterative aspect in Section II-A and its training data cleansing in Section II-E, must be assessed in terms of rate-distortion.

Given that the iterative training emerges as a solution to the blurriness of the trained neural network predictions, see Section I, it must be evaluated by using an objective function that does not reduce this blurriness while being very efficient in intra prediction. Thus, the objective function  $\mathcal{L}_{h,w}$  to be minimized over the parameters  $\theta_{h,w}$  of  $f_{h,w}(\cdot; \theta_{h,w})$  is built on the l2-norm of the difference between a  $w \times h$  block and its neural network prediction. Moreover, regularization via l2-

norm of the neural network weights  $\mathbf{W}_{h,w}$  applies [30].

$$\mathcal{L}(S_{h,w}; \theta_{h,w}) = \frac{1}{\text{card}(S_{h,w})} \sum_{(\mathbf{x}_c, \mathbf{y}_c) \in S_{h,w}} \left\| \mathbf{y}_c - \hat{\mathbf{y}}_c \right\|_2^2 + \lambda \|\mathbf{W}_{h,w}\|_2^2 \quad (1)$$

where  $\hat{\mathbf{y}}_c = f_{h,w}(\mathbf{x}_c; \theta_{h,w})$  and  $\lambda = 0.0005$ . As this paper does not address the neural network architectures, the experiments reuse the neural networks architectures, the distributions for initializing their parameters, and the training hyperparameters in [16].  $\Gamma$  combines the ILSVRC2012 [26] and DIV2K [31] training RGB images, converted into  $\text{YCbCr}$ . The implementation involves Tensorflow 1.9.0 [32]. For training, a GPU NVIDIA Tesla P100 is used.

Up to now, only the training phase of the neural networks has been covered. For the following experiments, details on the test phase must be specified. During the test phase, for a given  $w \times h$  block to be predicted, the preprocessing of its context and the postprocessing of the neural network prediction derive from the context preprocessing during the training phase. A single step is added to adjust to the codec internal bitdepth  $b \in \{8, 10\}$ . More specifically, the context  $\mathbf{X}$  of this block is divided by  $2^{b-8}$  and preprocessed as described by “mask” and “center” in Figure 4, yielding the preprocessed context  $\mathbf{X}_c^t$ . Then, the neural network prediction is postprocessed by adding the mean  $\mu$  of the available decoded pixels in  $\mathbf{X}$ , multiplying by  $2^{b-8}$ , and clipping to  $[0, 2^b - 1]$ , yielding the prediction

$$\hat{\mathbf{Y}} = \min(\max(2^{b-8}(f_{h,w}(\mathbf{X}_c^t; \theta_{h,w}) + \mu), 0), 2^b - 1).$$

Section II-F uses H.265 (HM-16.15). The signalling of the single additional neural network-based intra prediction mode in H.265 follows [16]. H.265 with the single additional mode is denoted H.265-ITNN, ITNN standing for Iteratively Trained Neural Networks. The test set gathers luminance images only as the neural networks are trained on pairs of a luminance block and its context and, to simplify the interpretation of the results, the intra prediction of chrominance blocks is temporarily set aside. Therefore, H.265-ITNN and H.265 encode the luminance channel of the first frame of video sequences from the Common Test Conditions (CTC) [33]. Note that the neural networks cannot specialize to the CTC video sequences as they do not belong to  $\Gamma$ . The rate-distortion performance is computed via the Bjontegaard metric [34] of H.265-ITNN with respect to H.265 with QP  $\in \{17, 22, 27, 32, 37, 42\}$ .

1) *Benefits of the iterative aspect:* To avoid mixing up the contributions of the iterative aspect and the training data cleansing to the rate-distortion performance, the dB-rate reductions in Table I are computed by eliminating the training data cleansing from the iterative training. This means that Algorithm 3 becomes equivalent to Algorithm 2, but substituting “codec” with “codecNN”.

The second training iteration yields  $-0.30\%$  of additional mean dB-rate reduction with respect to the first one. From the second iteration to the third one,  $-0.11\%$  of additional mean dB-rate reduction is obtained, see the last three columns of Table I. The benefits of the iterative training come from a change in the training data, not an underfitting at the first iteration. This is proved by two experimental pieces of

TABLE I: dB-rate reductions in % of H.265-ITNN after each iteration of the iterative training without the training data cleansing. The anchor is H.265. Only the luminance channel of the first frame of each video sequence is considered.  $(l, p)$  refers to the training using  $l$  iterations and, at each iteration, multiplying by  $p \in \mathbb{N}^*$  the number of training iterations at each stage of the learning rate scheduling.

Video sequence	dB-rate reduction of H.265-ITNN						
	(1, 2)	(1, 3)	(1, 1)	(2, 1)	(3, 1)		
A	CampfireParty	-3.32	-3.32	-3.38	-3.49	-3.58	
	DaylightRoad2	-3.96	-3.98	-3.95	-4.26	-4.51	
	Drums2	-4.68	-4.71	-4.67	-5.00	-5.03	
	Tango2	-6.36	-6.39	-6.36	-6.40	-6.54	
	ToddlerFountain2	-3.30	-3.40	-3.36	-3.48	-3.55	
	TrafficFlow	-4.29	-4.42	-4.48	-4.74	-4.91	
	PeopleOnStreet	-5.82	-5.81	-5.99	-6.15	-6.14	
	Traffic	-4.69	-4.71	-4.74	-4.96	-5.04	
	B	BasketballDrive	-7.09	-7.14	-7.25	-8.07	-8.37
		BQTerrace	-3.81	-3.79	-4.09	-4.66	-4.75
Cactus		-4.15	-4.08	-4.22	-4.61	-4.78	
Kimono		-3.89	-3.89	-3.89	-4.04	-4.08	
ParkScene		-2.82	-2.82	-2.91	-2.91	-2.95	
C	BasketballDrill	-4.68	-4.70	-4.81	-5.12	-5.24	
	BQMall	-3.93	-3.92	-3.96	-4.37	-4.56	
	PartyScene	-2.98	-2.99	-2.94	-3.19	-3.36	
	RaceHorses	-3.76	-3.73	-3.77	-4.12	-4.13	
D	BasketballPass	-4.49	-4.52	-4.10	-4.71	-4.88	
	BlowingBubbles	-3.17	-3.09	-3.25	-3.48	-3.52	
	BQSquare	-3.47	-3.46	-3.38	-3.78	-3.78	
	RaceHorses	-4.97	-4.96	-4.96	-5.29	-5.50	
Mean	-4.27	-4.28	-4.31	-4.61	-4.72		

evidence. Firstly, when  $l = 1$  and the number of training iterations at each stage of the learning rate scheduling is multiplied by  $p \in \{2, 3\}$ , almost no change in the mean dB-rate reduction is reported with respect to the case  $l = 1$  and  $p = 1$ , see the first three columns of Table I. Yet, the case  $l = 1$  and  $p = 3$  and the case  $l = 3$  and  $p = 1$  amount to the same number of training iterations. Besides, we have run the case  $l = 3$  and  $p = 1$  with the random initialization of the neural network parameters at each iteration. This means that, in Algorithm 1, the random initialization of the first minimization applies to all subsequent minimizations. In this case, negligible variations in dB-rate reductions with respect to those in the last column of Table I have been observed.

2) *Benefits of the training data cleansing:* Table II shows that, for  $l = 2$  and  $p = 1$ ,  $-0.48\%$  of additional mean dB-rate reduction is reported when the training data cleansing is turned on with respect to the case where it is turned off. For  $l = 3$  and  $p = 1$ , the additional mean dB-rate reduction reaches  $-0.46\%$ . Therefore, the iterative aspect and the training data cleansing have equally large impacts in terms of rate-distortion.

3) *Cumulated benefits:* Overall, the iterative training yields  $-0.87\%$  of additional mean dB-rate reduction compared to a single-step training, see the third column of Table I and the last column of Table II.

### G. Behavior of the modified codec through iterations

The rate-distortion benefits identified in Section II-F3 lead to the question of how the iterative training affects the codec with the single additional neural network-based mode.

TABLE II: dB-rate reductions in % of H.265-ITNN when the training data cleansing is turned off and on. The anchor is H.265. Only the luminance channel of the first frame of each video sequence is considered.

Video sequence	dB-rate reduction of H.265-ITNN					
	cleansing off		cleansing on			
	(2, 1)	(3, 1)	(2, 1)	(3, 1)		
A	CampfireParty	-3.49	-3.58	-3.62	-3.67	
	DaylightRoad2	-4.26	-4.51	-4.66	-4.63	
	Drums2	-5.00	-5.03	-5.22	-5.33	
	Tango2	-6.40	-6.54	-6.52	-6.54	
	ToddlerFountain2	-3.48	-3.55	-3.58	-3.67	
	TrafficFlow	-4.74	-4.91	-5.21	-5.40	
	PeopleOnStreet	-6.15	-6.14	-6.40	-6.47	
	Traffic	-4.96	-5.04	-5.32	-5.43	
	B	BasketballDrive	-8.07	-8.37	-8.83	-8.85
		BQTerrace	-4.66	-4.75	-5.26	-5.38
Cactus		-4.61	-4.78	-5.10	-5.10	
Kimono		-4.04	-4.08	-4.20	-4.19	
C	ParkScene	-2.91	-2.95	-3.01	-3.12	
	BasketballDrill	-5.12	-5.24	-6.48	-6.73	
	BQMall	-4.37	-4.56	-5.15	-5.18	
	PartyScene	-3.19	-3.36	-3.57	-3.71	
D	RaceHorses	-4.12	-4.13	-4.57	-4.55	
	BasketballPass	-4.71	-4.88	-6.31	-6.35	
	BlowingBubbles	-3.48	-3.52	-4.06	-4.09	
	BQSquare	-3.78	-3.78	-4.35	-4.50	
	RaceHorses	-5.29	-5.50	-5.57	-5.89	
Mean	-4.61	-4.72	-5.09	-5.18		

To answer this, let us first analyze how the neural network prediction evolves over iterations. This analysis requires to predict a given block from its context via a neural network after two different training iterations. But, within H.265-ITNN, the quantization noise in the context of this block varies over iterations as the codec intra prediction changes over iterations, making the predictions incomparable. That is why the first analysis is not performed inside H.265-ITNN. Instead, the following experiment acts as a substitute. Triplets of a  $w \times w$  block, its context, and its reference samples are extracted from the luminance channel of  $YCbCr$  images at random spatial locations. These images are obtained by converting into  $YCbCr$  the 24 RGB images in the Kodak suite [35] and the 100 RGB images in the BSDS test dataset [36]. Then, for each triplet, the two predictions of the block given by the neural network  $f_{w,w}(\cdot; \theta_{w,w}^{(i)})$  after the first and third training iterations, i.e.  $i \in \{0, 2\}$ , are compared to the prediction of the best H.265 intra prediction mode in terms of prediction PSNR.

Successful cases for the iterative training, i.e. with improvement of the quality of the neural network prediction over iterations, are illustrated by Figures 7, 9, and 11. Failure cases are depicted in Figures 8, 10, and 12. In all cases, the neural network prediction gets shaper over iterations. Note that this indicates that the training data cleansing reaches its goal.

In Figure 8, the predicted block given by the neural network after the first iteration and the one from the best H.265 mode are all black. But, after the third iteration, the bottom-right of the predicted block returned by the neural network contains an extrapolation of the diagonal bright gray border at the top-right of the context. In Figure 10, the predicted block provided by the neural network after the first iteration and the one from the best H.265 mode are all dark gray. However, after the third iteration, we see at the bottom-right



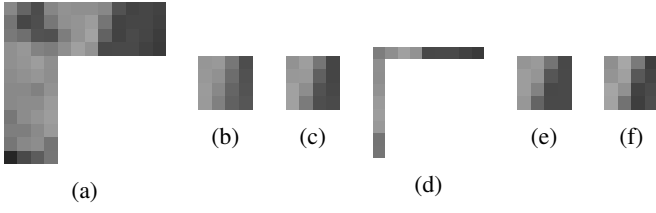


Fig. 7: Predictions of a  $4 \times 4$  luminance block: (a) context, (b) prediction from the context via the neural network after the first training iteration (PSNR = 23.74 dB), (c) prediction via the neural network after the third iteration (PSNR = 30.44 dB), (d) reference samples, (e) prediction from the reference samples via the best H.265 mode of index 30 in terms of prediction PSNR (PSNR = 28.79 dB), and (f) original block.

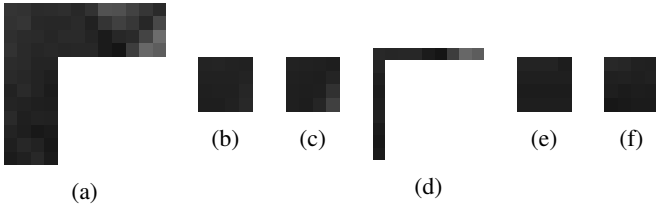


Fig. 8: Predictions of a  $4 \times 4$  luminance block: (a) context, (b) prediction from the context via the neural network after the first training iteration (PSNR = 33.60 dB), (c) prediction via the neural network after the third iteration (PSNR = 30.66 dB), (d) reference samples, (e) prediction from the reference samples via the best H.265 mode of index 10 in terms of prediction PSNR (PSNR = 38.30 dB), and (f) original block.

of the predicted block generated by the neural network an extrapolation of the diagonal bright gray border at the bottom of the context. Similarly, in Figure 12, the predicted block computed by the neural network after the first iteration looks blurry whereas, after the third iteration, it includes a black triangle, which contrasts with the predicted block from the best H.265 mode. According to the last three examples, the neural network can diverge from the best H.265 mode over iterations. Note that this suggests that the iterative aspect of the training actually achieves its target. Differently, in Figures 7 and 11, the predicted block given by the neural network comes closer to the one from the best H.265 mode over iterations. This convergence might stem from the very high likelihood of the best H.265 mode given the context of the block.

Given the conclusions of the last two paragraphs, in H.265-ITNN, if the context of a block contains a clear border along the frontier with this block, the single additional neural network-based mode should infer from the context a likely direction of propagation. It is either the correct direction and the prediction quality improves over iterations or an incorrect direction and the prediction quality degrades over iterations. That is why, on average, the frequency of selection of the single additional mode in H.265-ITNN should increase over iterations while those of the H.265 directional modes must decrease and those of PLANAR and DC should go up. This must be valid for small blocks at small QPs since the large blocks returned by the image partitioning at large QPs

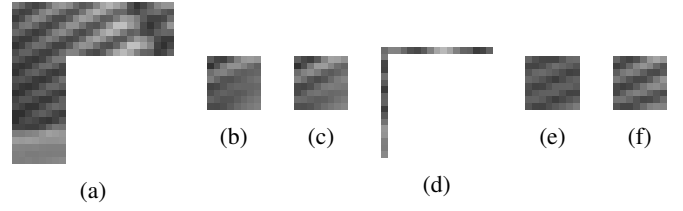


Fig. 9: Predictions of a  $8 \times 8$  luminance block: (a) context, (b) prediction from the context via the neural network after the first training iteration (PSNR = 23.71 dB), (c) prediction via the neural network after the third iteration (PSNR = 25.76 dB), (d) reference samples, (e) prediction from the reference samples via the best H.265 mode of index 6 in terms of prediction PSNR (PSNR = 20.94 dB), and (f) original block.

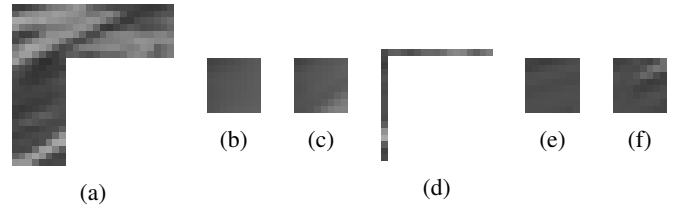


Fig. 10: Predictions of a  $8 \times 8$  luminance block: (a) context, (b) prediction from the context via the neural network after the first training iteration (PSNR = 24.45 dB), (c) prediction via the neural network after the third iteration (PSNR = 22.24 dB), (d) reference samples, (e) prediction from the reference samples via the best H.265 mode of index 7 in terms of prediction PSNR (PSNR = 27.63 dB), and (f) original block.

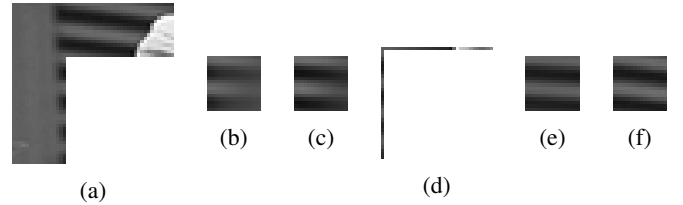


Fig. 11: Predictions of a  $16 \times 16$  luminance block: (a) context, (b) prediction from the context via the neural network after the first training iteration (PSNR = 22.85 dB), (c) prediction via the neural network after the third iteration (PSNR = 26.09 dB), (d) reference samples, (e) prediction from the reference samples via the best H.265 mode of index 11 in terms of prediction PSNR (PSNR = 28.05 dB), and (f) original block.

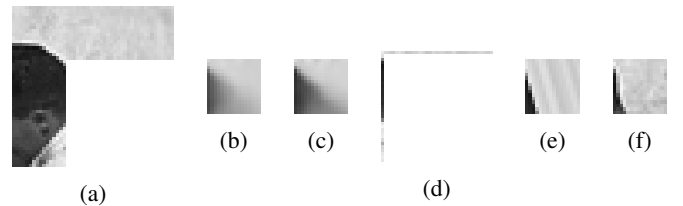


Fig. 12: Predictions of a  $16 \times 16$  luminance block. The legend in Figure 11 is replicated here, except that (b) PSNR = 16.06 dB, (c) PSNR = 13.05 dB, and (e) the best H.265 intra prediction mode in terms of prediction PSNR has index 23 and its prediction PSNR is equal to 21.83 dB.

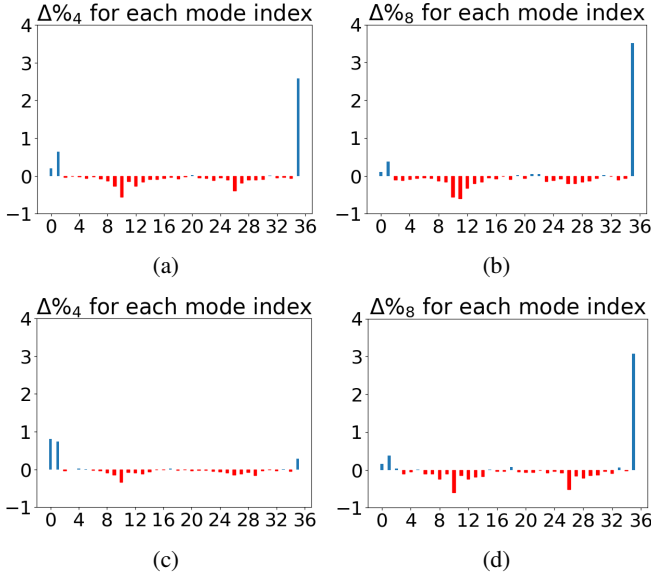


Fig. 13: Difference  $\Delta\%_w$  between the percentage of selection an intra prediction mode in H.265-ITNN after the third training iteration and that after the first training iteration on the  $w \times w$  blocks returned by the image partitioning: (a)  $w = 4$  and  $QP = 22$ , (b)  $w = 8$  and  $QP = 22$ , (c)  $w = 4$  and  $QP = 27$ , (d)  $w = 8$  and  $QP = 27$ . The index of the neural network-based mode is 35.  $\Delta\%_w$  is computed by averaging over the H.265-ITNN encodings of the 124  $YCbCr$  images used earlier.

sometimes exhibit complex textures, see Section II-B, and the behavior of a deep predictor on large blocks with diverse textures can hardly be forecast [10]. The previous assumption is verified by Figure 13. Therefore, for small blocks, the single additional neural network-based mode takes a growing proportion of frequency of selection away from the H.265 directional modes over iterations and, as its signalling cost is much smaller [16], bitrates are saved.

### III. SIGNALLING OF THE NEURAL NETWORK-BASED INTRA PREDICTION MODE IN H.266

Section II-F evaluates the rate-distortion performance of H.265 including the single additional neural network-based mode. Before assessing the rate-distortion performance of H.266 with the neural network-based mode, a signalling of this mode in H.266 must be developed.

The first principle of the proposed signalling addresses the large number of neural networks in H.266 incurring a large memory cost. Indeed, blocks of each possible size are predicted by a different neural network belonging to the neural network-based mode, see Section II. As the H.266 partitioning [25] can involve 25 different block sizes, the neural network-based mode in H.266 should be made of 25 neural networks. Note that the calculation of the previous figure excludes the option of splitting a luminance PB into multiple TBs because, as said in Section III-A, the combination of the neural network intra prediction and this type of split is not allowed. This contrasts with the H.265 partitioning involving 5 different block sizes, the neural network-based mode thus comprising

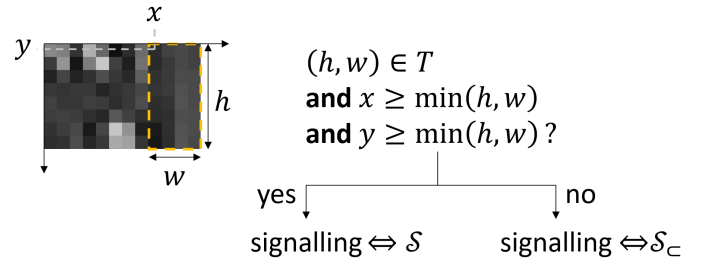


Fig. 14: Choice of the intra prediction mode signalling for the current  $w \times h$  luminance PB framed in orange. The first frame of “PartyScene” in 4:2:0 is being encoded via H.266-ITNN with  $QP = 37$ . The coordinates of the pixel at the top-left of the PB in the frame are  $x = 8$  and  $y = 0$ .  $h = 8$  and  $w = 4$ .

5 neural networks only. As a deep neural network for intra prediction has about  $10^6$  parameters [12], the memory cost of the parameters of 25 neural networks in H.266 seems to be too high. To reduce this cost, only blocks of some sizes are predicted via neural networks. For each of these sizes, the pair of the height and width is inserted into the set  $T \subseteq Q$ . Then, for the current block to be predicted, the neural network-based mode is signalled if it includes the neural network predicting blocks of the current block size.

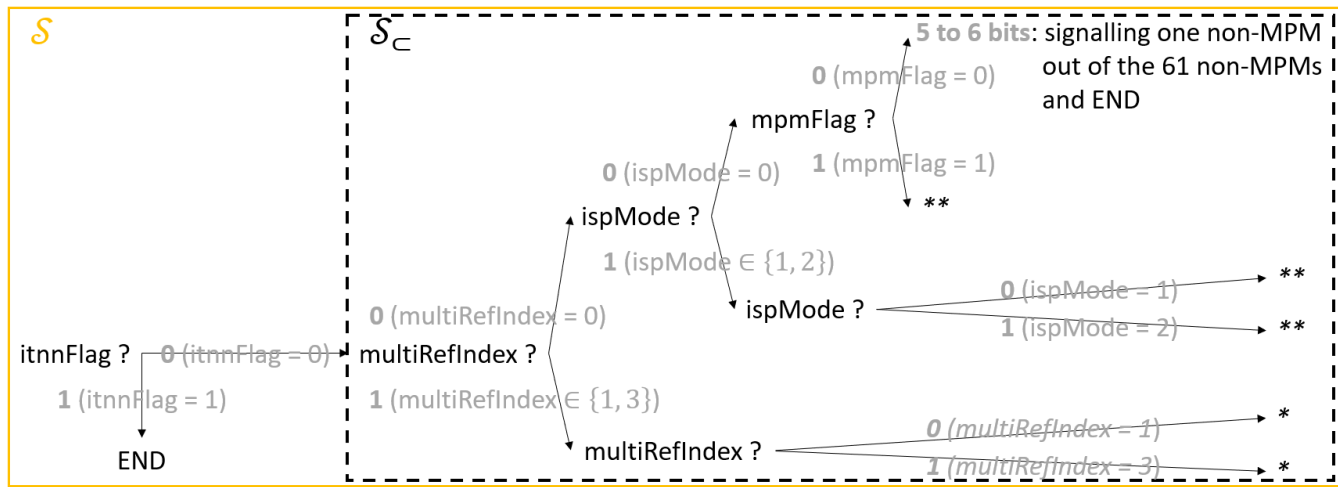
Furthermore, the neural network-based mode should not be signalled when the neural network prediction cannot be carried out as the context of the current block to be predicted goes out of the image bounds.

#### A. Signalling for a luminance PB

Given the above-mentioned two principles, for a  $w \times h$  luminance PB whose top-left pixel is located at  $(x, y)$  in the image, the intra prediction mode signalling  $\mathcal{S}$  including the flag *itnnFlag* of the neural network-based mode is chosen if  $(h, w) \in T$  and  $x \geq \min(h, w)$  and  $y \geq \min(h, w)$ . Otherwise, another intra prediction mode signalling  $\mathcal{S}_C$  which does not comprise *itnnFlag* applies, see Figure 14.

Moreover, as the neural network-based mode yields predictions of relatively good quality for a wide variety of luminance blocks [16], according to entropy coding, see Section 3.2 of [37], *itnnFlag* should be placed first in  $\mathcal{S}$ , see Figure 15. *itnnFlag* = 1 indicates that the neural network-based mode predicts the current luminance PB and its child TB(s).

The intra prediction of H.266 already features a machine learning approach, called Matrix Intra Prediction (MIP) [38]. MIP differs from our neural network-based mode in three main regards. Firstly, for a given  $w \times h$  luminance block, MIP only considers the  $w$  decoded pixels above this block and the  $h$  decoded pixels on its left side for intra prediction whereas, here, the context of this block contains  $\min(h, w) (\min(h, w) + 2w + 2h)$  decoded pixels. Secondly, MIP refers to a set of intra prediction modes, each mode predicting this block via a linear transformation of a down-sampled version of the  $w + h$  decoded pixels. Note that, in the version VTM-5.0, the transformation was affine whereas, since VTM-6.0, the transformation has been linear [39]. In contrast, our single additional mode relies on deep neural networks. Finally, MIP applies to luminance blocks exclusively whereas



\* **1 to 4 bits**: signalling one MPM out of the 5 possible MPMs and END

\*\* **1 to 5 bits**: signalling one MPM out of the 6 possible MPMs and END

Fig. 15: Decision tree illustrating the two intra prediction mode signalling  $\mathcal{S}$  and  $\mathcal{S}_C$  for the current luminance PB. For a given node, for each of the two choices, the bin value appears in bold gray and the flag/index value is in gray between brackets.

the single additional mode also applies to chrominance blocks, see Section III-B. As no other machine learning-based intra prediction tool than MIP and its predecessor [40] is currently put into H.266, H.266 with the neural network-based mode, called H.266-ITNN, will be compared to H.266 in terms of rate-distortion. To compare two codecs, each having a different machine learning-based intra prediction tool, MIP is removed from H.266-ITNN, see Figure 15.

Apart from removing MIP from H.266-ITNN, the core intra prediction signalling in VTM-5.0 is transferred to H.266-ITNN, see Figure 15. In Figure 15, *multiRefIndex* signals Multiple-Reference Lines (MRL), its values 0, 1, and 3 indicating the use of respectively the first, second, and fourth rows of decoded pixels above the current luminance block and columns of decoded pixels on its left side. *ispMode* signals Intra Sub-Partitions (ISP), its values 0, 1, and 2 referring to respectively no partitioning of the current luminance PB into multiple TBs, horizontal partitioning, and vertical partitioning [41]. *mpmFlag* tells whether the mode selected to predict the current luminance block belongs to the list of the 6 Most Probable Modes (MPMs) [42]. Note that the specifications in Figure 15 have changed since VTM-5.0. For instance, since VTM-7.0, ISP has been enabled with any of the 67 H.266 modes, whether this mode belongs to the list of MPMs or not.

In its present form, the intra prediction mode signalling in H.266-ITNN for the current luminance PB has a redundancy. Indeed, if the neural network-based mode predicts the PB above the current luminance PB or the one on its left side, the neural network-based mode appears in the MPMs of the current PB. Consequently, the neural network-based mode has two codewords: 1 and the codeword of a MPM. To remove this redundancy, each MPM being the neural network-based mode is replaced by the mode of index either 50, 18, 46, 54 or 34. This sequence is scanned until a mode that does not already belong to the list of MPMs is found. PLANAR and DC do not appear in this sequence as they are always MPMs.

### B. Signalling for a chrominance PB

As with luminance, the neural network-based mode gives predictions of correct quality for chrominance blocks with diverse textures, implying that its signalling cost must be low for chrominance too. As the flag of the Direct Mode (DM) comes first in the intra prediction mode signalling for a chrominance PB in VTM-5.0, see [43], we allow the neural network intra prediction of a chrominance PB via DM. Note that, since VTM-6.0, the DM flag has no longer been first in the intra prediction mode signalling for a chrominance PB since the CCLM flag has been placed before it [44].

But, the use of the neural network-based mode via DM is restricted by the two principles laid down at the beginning of Section III and the separation of the H.266 partitioning tree for luminance from that for chrominance, see Section 6.4 of [43]. To incorporate these constraints, for a given  $w \times h$  chrominance PB whose top-left pixel is at  $(x, y)$  in the image, if the luminance PB collocated with this chrominance PB is predicted by the neural network-based mode, DM becomes the neural network-based mode if  $(h, w) \in T$  and  $x \geq \min(h, w)$  and  $y \geq \min(h, w)$ . Otherwise, DM is set to PLANAR.

### C. Sizes of blocks predicted by the neural network-based mode

Now, only the set  $T$  of pairs of the height and width of the blocks that can be predicted by the neural network-based mode remains to be defined. Some preliminary tests have revealed that, for non-square blocks, when the neural network-based mode includes neural networks predicting relatively small blocks, e.g.  $4 \times 8$  blocks, and does not contain those predicting the large ones, e.g.  $8 \times 32$  blocks, the rate-distortion performance is slightly better compared to the other way round. By favoring the relatively small non-square blocks over the large ones,  $T = \{(4, 4), (4, 8), (8, 4), (8, 8), (16, 16), (4, 16), (16, 4), (8, 16), (16, 8), (32, 32), (64, 64)\}$ . Therefore, the neural network-based mode comprises 11 neural networks in H.266-ITNN.

#### IV. COMPARISON WITH THE STATE-OF-THE-ART

Now that the iterative training of neural networks for intra prediction is explained, see Section II, and the single additional mode involving the trained neural networks can be integrated into both H.265 and H.266, see Section III, the two codecs with the single additional mode, namely H.265-ITNN and H.266-ITNN, can be compared against the state-of-the-art.

##### A. Comparison for H.265

In the literature on the enhancement of the H.265 intra prediction via neural networks, Progressive Spatial Recurrent Neural Network (PS-RNN) [17] and Intra Prediction Fully-Connected Networks (IPFCN) [12] stand out as the two benchmarked approaches. For comparison, the experimental setups shared by both methods is reproduced here. Precisely, only the first frame each video sequence from the classes B, C, and D of the CTC [33] is considered. The rate-distortion performance of H.265 including a neural network-based intra predictor is calculated via the Bjontegaard metric of this modified version of H.265 with respect to H.265 with  $QP \in \{22, 27, 32, 37\}$ . All intra is used as configuration.

Unlike our iterative training, the trainings of PS-RNN and IPFCN have a single step. But, IPFCN comes in two variants, namely Intra Prediction Fully-Connected Networks Single (IPFCN-S) and Intra Prediction Fully-Connected Networks Dual (IPFCN-D), the latter featuring an enhanced training process. Indeed, in IPFCN-S, four fully-connected networks are designed to predict blocks of sizes  $4 \times 4$ ,  $8 \times 8$ ,  $16 \times 16$ , and  $32 \times 32$  respectively. Then, each neural network is trained on pairs of a luminance block returned by the H.265 partitioning of images and its context. Finally, the four trained neural networks are aggregated into a neural network-based mode in H.265. In contrast, in IPFCN-D, the above-mentioned set of fully-connected networks is duplicated into two sets. Then, the different pairs of a luminance block given by the H.265 partitioning of images and its context are clustered into two groups, the first one gathering the blocks predicted via either PLANAR or DC and the second one containing those predicted via a directional mode. Each of the two sets of neural networks is trained on a different cluster. In the end, the two sets of trained neural networks form the neural network-based mode in H.265. As IPFCN-D outperforms IPFCN-S in terms of rate-distortion [12], IPFCN-D is picked for comparison.

Table III shows that, for the luminance channel, H.265-ITNN using three training iterations yields  $-1.8\%$  of additional mean dB-rate reduction compared to IPFCN-D. With respect to PS-RNN, the additional mean dB-rate reduction reaches  $-1.9\%$ . Note that, if the number of training iterations is reduced to one, the mean dB-rate reduction of H.265-ITNN dips to  $-3.3\%$ . Therefore, the benefits of the iterative training on luminance only and those on  $YC_bC_r$  look consistent.

##### B. Comparison for H.266

Currently, MIP seems to be the only benchmarked machine learning-based tool for improving the H.266 intra prediction, see Section III-A. As H.266 includes MIP since VTM-5.0, the

evaluation of H.266-ITNN, which does not contain MIP, with respect to VTM-5.0 establishes a direct comparison between our single additional neural network-based mode and MIP. The experimental protocol in this section takes the protocol from Section IV-A, except that eight video sequences from the class A of the CTC are added in order to diversify the test data.

Due to the increase of encoding time from H.265 to H.266, the commonly used deep neural networks for intra prediction cannot currently be trained in reasonable time via the proposed iterative training with H.266 as codec. Indeed, even though the encoding time of H.265-ITNN is 50 times larger than that of H.265 [16], the encoding of  $\Gamma$  via H.265-ITNN does not exceed 4 days using 400 cores. However, as the ratio between the encoding time of H.266 (VTM-5.0) and that of H.265 (HM-16.15) is equal to 18, the encoding of  $\Gamma$  via H.266 with the neural network-based mode is estimated to 72 days using 400 cores. This is the current limitation of the iterative training. Two solutions could be the optimization of the neural network architectures for faster inference [45], [46] and the implementation of heuristics for H.266 encoder acceleration. But, these heuristics have not been developed yet since the H.266 standard is not finalized yet. For now, the models trained iteratively with H.265 as codec can be inserted into H.266 at test time. Therefore, the following experiments involves two versions of H.266-ITNN. For the “true” H.266-ITNN, blocks of sizes  $4 \times 4$ ,  $8 \times 8$ ,  $16 \times 16$ , and  $32 \times 32$  are predicted by the four neural networks trained iteratively with H.265 as codec and  $l = 3$ , the blocks of sizes  $8 \times 4$ ,  $4 \times 8$ ,  $16 \times 4$ ,  $4 \times 16$ ,  $16 \times 8$ ,  $8 \times 16$ , and  $64 \times 64$  being predicted by neural networks trained as described in [16]. For the second version, called H.266-STNN, any block whose pair of height and width belongs to  $T$  is predicted by a neural network trained as in [16]. STNN stands for Simply Trained Neural Networks.

H.266-ITNN gives  $-0.22\%$  of additional mean-dB rate reduction with respect to H.266-STNN, see Table IV. Thus, a noticeable improvement of the rate-distortion performance of H.266 with the neural network-based mode can be attributed to the iterative training whereas only a relatively small fraction of the blocks are actually predicted by iteratively trained neural networks. By extending the iterative training to the 11 neural networks in H.266-ITNN, a much larger increase in mean dB-rate reduction can be expected. Moreover, Table IV reports a mean dB-rate reduction of  $-1.92\%$  for H.266-ITNN. This experimental result shows the advantage of the single additional deep neural network-based mode over the multiple MIP modes. A visualization of reconstruction via H.266-ITNN is displayed in Figure 16.

To assess the net benefit of the single additional neural network-based mode to H.266, the anchor can now be set to VTM-5.0 with MIP off. The mean dB-rate reduction of H.266-ITNN becomes  $-2.28\%$ , see Table V.

##### C. Complexity

As the neural network architectures are taken from [16], the encoding and decoding times of a codec with the neural network-based mode with respect to those of the initial codec are comparable to the ones in [16].

TABLE III: dB-rate reductions in % of H.265-ITNN with  $l = 3$ , PS-RNN, and IPFCN-D. The anchor is H.265 (HM-16.15). Only the first frame of each video sequence is considered. All dB-rate reductions have one decimal digit, similarly to [12]. The largest dB-rate reduction in absolute value for the luminance channel is shown in bold.

Video sequence		our H.265-ITNN			PS-RNN [17]			IPFCN-D [12]		
		Y	C <sub>b</sub>	C <sub>r</sub>	Y	C <sub>b</sub>	C <sub>r</sub>	Y	C <sub>b</sub>	C <sub>r</sub>
B	BasketballDrive	<b>-8.5</b>	-9.7	-9.5	-1.4	-1.1	-1.4	-3.6	-2.9	-2.7
	BQTerrace	<b>-4.1</b>	-4.4	-4.0	-2.4	-0.5	-0.5	-2.1	-1.3	-0.5
	Cactus	<b>-4.2</b>	-4.1	-4.2	-2.3	-1.5	-0.9	-3.2	-1.8	-1.5
	Kimono	<b>-3.2</b>	-3.8	-2.9	-1.2	-0.9	-0.9	-3.1	-2.1	-1.5
	ParkScene	-2.3	-4.0	-3.4	-2.7	-1.6	-1.3	<b>-3.6</b>	-2.2	-2.4
C	BasketballDrill	<b>-5.6</b>	-7.9	-7.1	-1.6	-0.3	-1.5	-1.5	-3.3	-2.2
	BQMall	<b>-4.1</b>	-5.0	-5.5	-3.0	-1.4	0.0	-2.2	-1.9	-1.0
	PartyScene	<b>-3.0</b>	-3.0	-2.8	-2.5	-2.2	-2.2	-1.6	-1.2	-0.1
	RaceHorses	<b>-3.8</b>	-4.1	-3.2	-2.3	-1.8	-1.0	-3.2	-1.9	-2.8
D	BasketballPass	<b>-3.8</b>	-4.3	-4.1	-2.1	-1.9	-0.5	-1.2	-0.3	1.1
	BlowingBubbles	<b>-3.0</b>	-5.2	-4.3	-2.7	-2.2	0.5	-1.9	-2.8	-3.5
	BQSquare	<b>-3.3</b>	-2.0	-1.9	-2.1	-0.6	1.8	-0.9	-0.1	-2.8
	RaceHorses	<b>-5.3</b>	-5.3	-6.3	-3.5	-3.3	-1.8	-3.2	-2.6	-2.8
Mean	<b>-4.2</b>	-4.8	-4.5	-2.3	-1.5	-0.7	-2.4	-1.9	-1.7	

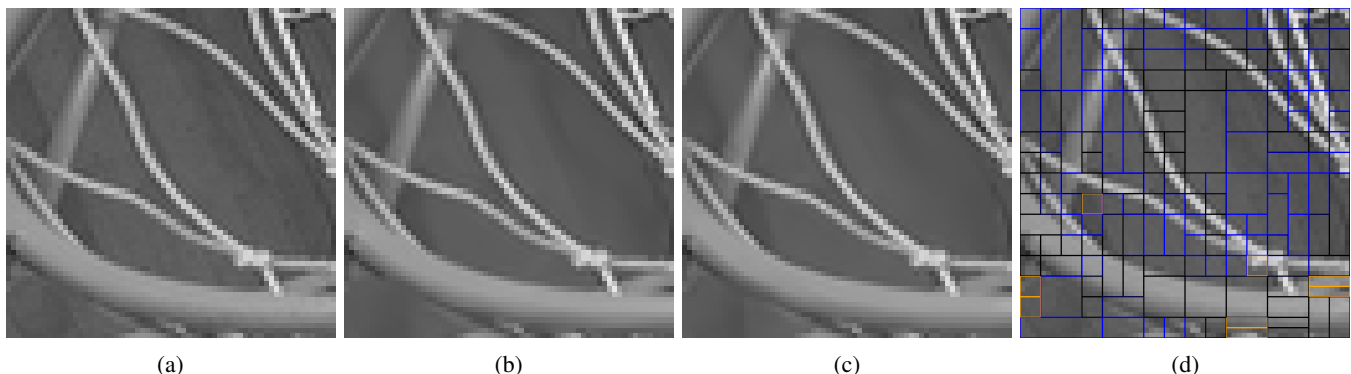


Fig. 16: Comparison of (a) the  $64 \times 64$  block whose top-left pixel is at  $(64, 64)$  in the luminance channel of “BasketballDrill”, (b) its reconstruction via VTM-5.0, (c) its reconstruction via H.266-ITNN, and (d) its partitioning via H.266-ITNN. QP = 27. In (d), the mapping from the color of the frame of the block to the intra prediction mode of the block is “orange”  $\rightarrow$  either PLANAR or DC, “black”  $\rightarrow$  directional mode, and “blue”  $\rightarrow$  neural network-based mode. For the entire luminance channel, for VTM-5.0, rate = 0.310 bpp and PSNR = 39.503 dB. For H.266-ITNN, rate = 0.305 bpp and PSNR = 39.491 dB.

TABLE IV: dB-rate reductions in % of H.266-STNN and H.266-ITNN. The anchor is H.266 (VTM-5.0). Only the first frame of each video sequence is considered. The largest dB-rate reduction in absolute value for the luminance channel is displayed in bold.

Video sequence		H.266-STNN			H.266-ITNN			
		Y	C <sub>b</sub>	C <sub>r</sub>	Y	C <sub>b</sub>	C <sub>r</sub>	
A	CampfireParty	-1.16	-0.53	-0.30	<b>-1.29</b>	-0.61	-0.25	
	DaylightRoad2	-1.76	0.57	-2.32	<b>-2.04</b>	-1.00	-1.58	
	Drums2	-1.44	-1.64	-1.03	<b>-1.63</b>	-1.76	-1.10	
	Tango2	-2.54	-2.35	-1.96	<b>-2.95</b>	-2.09	-3.03	
	ToddlerFountain2	-1.45	-2.25	-1.00	<b>-1.56</b>	-2.07	-1.31	
	TrafficFlow	-1.09	0.83	0.20	<b>-1.45</b>	1.57	0.58	
	PeopleOnStreet	-2.68	-3.27	-2.88	<b>-2.84</b>	-2.90	-3.15	
	Traffic	-1.87	-1.52	-1.30	<b>-1.97</b>	-1.62	-1.90	
	B	BasketballDrive	-1.84	-1.75	-2.15	<b>-2.03</b>	-1.34	-2.22
		BQTerrace	-1.58	-0.51	-0.65	<b>-1.75</b>	-0.22	-1.67
Cactus		-1.76	-0.81	-1.48	<b>-2.00</b>	-1.38	-1.65	
Kimono		-1.38	-2.56	-1.94	<b>-1.48</b>	-2.72	-2.51	
ParkScene		-1.18	-1.65	-2.08	<b>-1.22</b>	-0.71	0.45	
C		BasketballDrill	-1.06	0.65	-0.41	<b>-1.26</b>	0.50	-1.94
	BQMall	-2.21	-1.80	-1.89	<b>-2.60</b>	-1.14	-1.11	
	PartyScene	-1.96	-3.16	-0.88	<b>-2.15</b>	-2.88	-1.32	
	RaceHorses	-1.84	-0.34	-1.86	<b>-1.90</b>	-1.18	0.09	
	D	BasketballPass	-1.19	-3.41	-4.13	<b>-1.73</b>	-0.46	-3.02
BlowingBubbles		-1.80	-0.64	-0.10	<b>-2.05</b>	-1.65	1.00	
BQSquare		-1.86	0.96	-2.54	<b>-2.13</b>	1.63	-2.98	
RaceHorses		-2.00	-3.67	-1.15	<b>-2.27</b>	-1.90	-1.88	
Mean		-1.70	-1.37	-1.52	<b>-1.92</b>	-1.14	-1.45	

TABLE V: mean dB-rate reduction per class in % of VTM-5.0 with MIP on and H.266-ITNN. The anchor is VTM-5.0 with MIP off. Only the first frame of each video sequence is considered. The largest mean dB-rate reduction in absolute value for the luminance channel is written in bold. “Mean” refers to an average over video sequences, not over classes.

Class	VTM-5.0 with MIP on			H.266-ITNN		
	Y	C <sub>b</sub>	C <sub>r</sub>	Y	C <sub>b</sub>	C <sub>r</sub>
A	-0.37	-0.05	-0.16	<b>-2.36</b>	-1.35	-1.63
B	-0.34	-0.05	0.33	<b>-2.03</b>	-1.32	-1.18
C	-0.28	-0.65	-0.75	<b>-2.26</b>	-1.81	-1.83
D	-0.41	-0.56	0.19	<b>-2.49</b>	-1.23	-1.49
Mean	-0.35	-0.26	-0.09	<b>-2.28</b>	-1.41	-1.54

## V. CONCLUSION

This paper has introduced an iterative training of neural networks for intra prediction in a block-based codec. At each iteration, the neural networks become more beneficial intra predictors for this codec as the training sets are filled with pairs of a block and its context typically found in the codec image partitioning and for which the neural network intra prediction can outdo the codec intra prediction. When inserted into both H.265 and H.266, the iteratively trained neural networks bring significant improvements in terms of rate-distortion.

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