Data Clustering-Driven Neural Network for Intra Prediction

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Abstract—As a crucial part of video compression, intra prediction utilizes local information of images to eliminate the redundancy in spatial domain. In both H.265/HEVC and H.266/VVC, multiple directional prediction modes are employed to find the texture trend of each small block and then the prediction is made based on reference samples in the selected direction. Recently, the intra prediction schemes based on neural networks have achieved great success. In these methods, the networks are trained and applied to intra prediction in addition to the directional prediction modes. In this paper, we propose a novel data clustering-driven neural network (dubbed DCDNN) for intra prediction, which can learn deep features of the clustered data. In DCDNN, each network can be split into two networks by adding or subtracting Gaussian random noise. Then a data clustering-driven training iteration is applied to train all the derived networks recursively. In each iteration, the entire training dataset is partitioned according to the recovery qualities of the derived networks. For the experiment, DCDNN is implemented into HEVC reference software HM-16.9. The experimental results demonstrate that DCDNN can reach an average of 4.2% Bjontegaard distortion rate (BD-rate) improvement (up to 7.0%) over HEVC with all intra configuration. Compared with existing fully connected network-based intra prediction methods, the bitrate saving performance is further improved.

Index Terms—Video coding, intra prediction, neural network, data clustering.

I. INTRODUCTION

As the state of the art video coding standard, H.265/HEVC [1] laid down by Joint Collaborative Team on Video Coding (JCT-VC) could achieve approximately 50% bitrate saving for equivalent perceptual quality compared with the previous standard with computational complexity increase as a trade-off [2]. Especially, the bitrate saving provided by intra coding of HEVC is 22% on average, and up to 36% over H.264/AVC [3]. [4]. The improvement is mainly achieved by the more flexible block partition and the increased angular-prediction-mode granularity.

As a crucial part of intra prediction, the angular-prediction-mode granularity can greatly influence the intra prediction performance. In HEVC, the number of intra directional prediction modes is increased to 35. Compared with AVC, which only supports 9 intra directional modes, HEVC can utilize more spatial information because of the further detailed direction division. It could help to describe the directional patterns in local areas more precisely and thus give more reasonable prediction results. In the recently released H.266/VVC [5], the number of intra directional modes is increased to 67 [6].

Although more angular modes can make intra prediction more accurate, it is still challenging to predict blocks with complex patterns, especially the blocks without obvious directional features. This is because the directional prediction modes are all designed manually and almost equidistantly distributed with a certain direction. What’s more, for each mode, only a few reference pixels in a specific direction can be accessed and only simple linear interpolation is performed for prediction.

Recently, deep learning-based video coding has been developed rapidly. For the hybrid video coding framework, the deep tools are integrated into every single component [7], for example, intra prediction [8] - [14], inter prediction [15], [16], in-loop filtering [17] - [19], entropy coding [20], [21], and post-processing [22], [23]. For inter prediction, Yan et al. [15] proposed a fractional-pixel reference generation convolutional neural network (CNN) for both uni-directional and bi-directional motion compensation. To improve the bi-prediction performance, Zhao et al. [16] designed an enhanced bi-prediction scheme based on the CNN to generate predicted blocks in a non-linear fashion to improve the coding performance. For in-loop filtering, neural networks either act as additional tools to improve the performance of filtering [17], [18], or substitute the deblocking filter and the sample adaptive offset [19]. Deep networks could also be adopted as entropy coding tools to estimate the probabilities of predefined syntax elements, for example quantized coefficient [20] and transform index [21]. On the decoder side, deep learning-based post-processing tools are applied to improve reconstruction quality [22], [23].

In the existing deep learning-based intra predictions, the networks either directly produce prediction pixels [8], [9], [12] - [13] or enhance the prediction quality [10], [11] using available reference samples. In [10] and [11], the well-trained CNNs are added after the intra prediction module to refine the prediction output. In [8], different classes of block-context pairs defined by a known context-block relationship are used to train different neural networks. In [12], more network modes (up to 35) are designed for blocks of different sizes, and the architectures of networks are further simplified.

In this paper, a data clustering-driven neural network (DCDNN) is proposed for intra prediction, which can learn the deep features of the clustered data. In DCDNN, each network can be split into two networks by adding or subtracting...
Gaussian random noise. A K-means-like [24] data clustering-driven training [17] is applied to train all the derived networks recursively. The number of network modes in DCDNN could be controlled flexibly by observing the training loss before and after each split to decide if the split is beneficial for prediction. The experimental results show that DCDNN could provide an average of 4.2% bitrate saving compared with HM-16.9 [25] (up to 7.0%). Compared with IPFCN in [8] and methods in [12] - [14], DCDNN trains the networks by the data clustering-driven method, in which the training data is clustered in an unsupervised manner.

The rest of the paper is organized as follows. Section II provides a brief overview of related works, including intra prediction in HEVC and VVC, and deep learning-based intra prediction. The proposed DCDNN is detailed in Section III. In Section IV, the experimental results and analysis are presented. Finally, the conclusion and future works are provided in Section V.

II. RELATED WORKS

In this section, the intra predictions in HEVC and the newly released H.266/VVC [5] are first presented. Then the related deep learning-based intra predictions are reviewed.

A. Intra Prediction

In H.265/HEVC, the quadtree-based block partition is adopted for intra prediction and transformation. Each picture is divided into disjoint square coding tree units (CTUs) of the same size, each of which serves as the root of a block partition quadtree structure. Along the coding tree structure, the CTUs can be subdivided into coding units (CUs). A CU can be further split along the coding tree structure into smaller prediction units (PUs) which share the same prediction information, and transform units (TUs) which serve as the transformation units. In HEVC, there are 35 intra prediction modes, including planar mode, DC mode, and 33 angular modes. Planar mode is designed for areas with gradually changing contents. DC mode aims to predict smooth textures, and the predicted sample values are populated with a constant value representing the average of all surrounding reference samples. Angular modes are designed to model structures with directional edges.

In VVC, the concept of CU, PU, and TU are replaced by CU. A more advanced block partition mechanism with embedded multi-type trees (MTT), including quadtree (QT), binary tree (BT), and ternary tree (TT), is adopted [26]. Therefore, rectangular blocks are supported in VVC. In VVC, the number of angular modes is increased to 65 to better adapt to the diverse contents and different block sizes. By increasing the angular-prediction-mode granularity, more spatial information could be utilized to describe the directional patterns in local areas more precisely and therefore give more reasonable prediction results. In VVC, multiple reference lines are utilized as the reference candidates [27]. In addition, aiming at the problem of asymmetric distribution of direction prediction in the rectangular prediction unit, VVC integrates wide angular intra prediction (WAIP) [28] to further optimize the prediction.

Fig. 1: Intra prediction modes with the associate displacement values in HEVC and VVC. The red and green solid lines represent the vertical modes and the horizontal modes that exist in both HEVC and VVC. Mode represented by dotted lines only exists in VVC. Mode 0 is planar mode and mode 1 is DC mode.

The schematic diagram in Fig. 1 shows the directional modes in HEVC and VVC. As shown in Fig. 1 all directional prediction modes are designed to be almost equidistantly distributed with a certain direction. However, it is still challenging to predict blocks with complex patterns, especially the blocks without obvious directional features.

B. Deep Learning-Based Intra Prediction

Recently, deep learning-based video coding has been developed rapidly. The neural network-based intra prediction offers a reliable solution to the above-mentioned challenge. Some investigations on deep learning-based intra prediction have been carried out. Due to the correlation between the target block and the surrounding available reference pixels, the texture features of the local area can be learned through neural networks for more accurate prediction.

In [8], a fully connected network-based intra prediction (IPFCN) is proposed to learn an end-to-end mapping from neighboring reconstructed pixels to the target block. The neural networks are fed by 8 reference lines above and on the left side of the target block. The output of each network is the prediction result of pixels in raster order in the spatial domain. IPFCN-S has a single network that is trained utilizing an unclassified dataset, while IPFCN-D has two networks that are trained by the data from the non-angular modes (DC and Planar) and the other angular modes separately. IPFCN-S and IPFCN-D could achieve 2.6% and 3% bitrate saving, respectively.

In [12], different numbers of networks (up to 35) are designed for blocks with different sizes. All proposed neural networks for a given block size share all but the last layer. The network mode signaling is based on a sorted mode list, which
is produced by another fully connected network. Compared with IPFCN, the networks’ architecture is simplified to meet the low complexity requirement of VVC. The bitrate saving in [12] is around 2.5%. In a later version [13], each network has only one layer without non-linear activation, i.e. each network is reduced to a matrix plus a bias vector. Only one row and one column from the reconstructed picture are used as reference pixels, and only half of the pixels in the target block are generated by the selected network. The remaining half is generated by linear interpolation. This matrix-based intra prediction (MIP) has been adopted by VVC with a bitrate saving of 0.79% under all-intra configuration. In [14], a novel training loss function that reflects properties of the residual quantization and coding stages is designed by applying the $L1$-norm and a sigmoid-function to the prediction residual in the DCT domain. It could achieve a bitrate saving of 3.79% compared with VTM 1.0.

Deep learning could also be utilized for prediction result refining. In [10], a convolutional neural network-based intra prediction is proposed. The block size is constrained as $8 \times 8$. After HEVC intra prediction, the target block, along with its three nearest reconstruction blocks, forms a $16 \times 16$ block as the input of CNN. The output of the neural network is a residual block of the same size as the input. By subtracting the generated residual block from the original HEVC prediction result, the prediction quality can be enhanced. MSCNN proposed in [11] further improves this method by increasing the number of supported block sizes (i.e. $4 \times 4$, $8 \times 8$, $16 \times 16$, and $32 \times 32$). In addition, the multi-scale feature extraction is proposed to take advantage of feature maps in different scales to improve performance. MSCNN could achieve an average of 3.4% bitrate saving with all intra configuration.

In this paper, a data clustering-driven neural network (dubbed DCDNN) is proposed for intra prediction. In DCDNN, each network can be split into two networks by adding or subtracting Gaussian random noise. Then a data clustering-driven training is applied to train all the derived networks recursively. In each iteration, the entire training dataset is partitioned according to the recovery qualities of the derived networks.

## III. DATA CLUSTERING-DRIVEN NEURAL NETWORKS

In this section, the network split is firstly introduced. Then the network structure of DCDNN is presented. After that, the data clustering-driven training is described. Finally, the details of how to integrate DCDNN into the HEVC reference framework are provided.

### A. Network Split

In traditional LGB (Linde-Buzo-Gray) data clustering algorithm [30], a perturbation is produced and applied as an addition and subtraction term for splitting one clustering centroid into two. Inspired by this approach, we design a network split method to derive two networks from one network. However, instead of generating a perturbation by multiplying the original vector with a fixed perturbation coefficient as in LGB, in DCDNN, each network is split into two networks by adding or subtracting Gaussian random noise to each layer to randomly enhance and suppress the effect of the network nodes. The variance of the introduced Gaussian random noise is decided by the weights of each layer so that the mapping from the input to the output in the subsequent activation function will not be changed. In this way, two opposite displacements relative to the original output could be obtained. The two derived networks have the same structure and similar competitiveness. The network split is shown in Fig. 2.

After the network split, a data clustering-driven training is applied to train all the derived networks recursively. If more networks are needed, each network can be split into two networks again. By observing the training loss before and after each split, we can decide whether the split should be terminated.

### B. The Network Structure of DCDNN

The network structure of DCDNN is shown in Fig. 3. DCDNN consists of four parts: the input layer, the output layer, the fully connected layers, and the non-linear activation layers. The network input is the reconstructed reference samples surrounding the target block. To utilize more spatial contextual information for more accurate prediction, the multi-reference-line scheme [31] is employed, thus the network input is a $4NL + L^2$ vector, where $N \times N$ is the size of the target block and $L$ is the number of reference lines. If some required reference pixels are not available, the vacancies are filled in through a substitution manner which is the same as that of HEVC reference sample generation [32]. The network output is an $N \times N$ vector, corresponding to the predicted pixels of the target block in raster order.

In the DCDNN model, all linear layers are fully connected. Except for the last fully connected layer, all fully connected layers are with the same output dimension. If the depth of the neural network is denoted as $D$, the output of the $i$th linear layer would be:

$$Output_i = W_i \times Input_i + b_i, \quad 0 \leq i \leq D,$$

![Fig. 2. Network split.](image-url)
in which $W$ and $b$ represent the weights and bias, respectively. In addition, except for the last fully connected layer, each fully connected layer is followed by a non-linear activation layer. In this paper, PReLU (Parametric Rectified Linear Unit) [33] is selected as the activation function. PReLU is formulated as:

$$Output_k = \begin{cases} \text{Input}_k, & \text{if } \text{Input}_k \geq 0 \\ a_k \text{Input}_k, & \text{if } \text{Input}_k < 0 \end{cases}$$  

in which $\text{Input}_k$ and $Output_k$ represent the $k$th component of the activation layer’s input and output vectors, respectively. Similar to Leaky ReLUs activation function [34], if the input is positive, the activation layer’s output remains the same as the input. Otherwise, a factor should be applied to scale the input. The advantage is that the scale factor $a_k$ in PReLU can be learned and updated during the training process instead of being fixed as in Leaky ReLU. This attribute provides the possibility of the input and the output with different signs, thereby improving network prediction flexibility and enhancing prediction accuracy.

In this paper, the number of reference lines $L$ is set as 8, and the network depth $D$ is set as 4. Different networks are designed for blocks of different sizes. In HEVC, the luma TU’s size ranges from $4 \times 4$ to $32 \times 32$. The layer dimensions of networks are set to be 128, 256, 256, 512 for $4 \times 4$, $8 \times 8$, $16 \times 16$, and $32 \times 32$ blocks, respectively.

**C. Data Clustering-Driven Training of DCDNN**

In DCDNN, a data clustering-driven training is applied to recursively train all the derived networks for intra prediction. In [24], a K-means clustering algorithm is proposed for data classification. The similarity between data is measured by Euclidean distance. In [17], a K-means-like training strategy is applied for training content-aware convolutional neural networks for HEVC in-loop filtering. Inspired by [17], in DCDNN, the entire training dataset is partitioned according to the recovery qualities of the derived networks in each iteration. Then the partitioned training samples are fed into the corresponding networks for training. Fig. 4 is an example of the training dataset partition, network split, and the network training. The circles filled with a specific colour represent the data for training and the triangle filled with the same colour represents the corresponding network.

1) **Training Dataset Partition**: In DCDNN, the derived networks are taken as the clustering centers and the similarity between data is measured through the recovery qualities of the derived networks. In each iteration, the recovery qualities of each data through all the derived networks are calculated separately, and the data is grouped into the cluster with the best recovery quality.

DCDNN follows the mode decision method in HEVC and determines the best intra prediction mode at the PU level. It means TUs with different sizes in each PU share the best DCDNN prediction mode. Therefore, the squared error between original pixels and the prediction is summed over each pixel of the PU to measure the recovery quality, even though the basic processing unit is TU. Only the recovery quality of the luma component is considered here since the best intra mode is only decided by the luma component. Fig. 5 is an example of the prediction loss calculation of a $64 \times 64$ PU.

2) **Network Training**: After the training dataset partition, the partitioned datasets are fed into the corresponding derived networks for training. As shown in Fig. 4, the displacements of the clustering centers reflect the networks’ parameters update. The parameter set $\Theta = \{W, b, a\}$ in the fully connected layers and the activation layers is tuned continuously to learn the mapping from the surrounding reference samples to the target block. Given a collection of $M$ training sample pairs, by minimizing the loss between the network output $F(x_j|\Theta)$ and the ground truth $y_j$, the network’s prediction ability could be progressively enhanced. Meanwhile, a penalty term is added to avoid over-fitting and improve the generalization ability of DCDNN. Thus the loss function is followed by an $L2$ regularization term. The loss function is formulated as:

$$L(\Theta) = \frac{1}{2M} \sum_{j=1}^{M} \|F(x_j|\Theta) - y_j\|^2 + \frac{\nu}{2} \|\Theta\|^2,$$  

Fig. 3. The network structure of DCDNN.

Fig. 4. An example of the training dataset partition, the network split, and the network training.
where \( \gamma \) represents the weight of the \( L2 \) regularization term, and it is set to be \( 10^{-4} \) in the experiments. For the initialization of the parameter set \( \Theta \), the weights \( W \) are randomly generated from a Gaussian distribution with a mean of 0 and standard deviation of 1. The bias \( b \) and the scale factor \( a \) are initialized as 0 and 0.25, respectively. The optimization algorithm to update all parameters is the stochastic gradient descent (\( SGD \)) with a momentum term [35]. The momentum of \( SGD \) optimization is set as 0.9. The learning rate decays exponentially from \( 10^{-1} \) to \( 10^{-5} \) to ensure that the model does not fluctuate too much in the later stages of training, thereby closer to the optimal solution.

Compared with [8] and methods in [12] - [14] that use datasets classified by predefined features for network training, DCDNN trains the networks by the data clustering-driven method, in which the training data is clustered in an unsupervised manner. The learned deep texture features are not necessarily directional anymore.

3) **Overall Training:** In the beginning, a DCDNN network is pre-trained. The base learning rate is set to \( 10^{-1} \) as recommended in [8], [11], [17]. The network is trained with a fixed learning rate for 10 epochs and then use the exponentially decaying learning for another 10 epochs until its convergence. In our experiments, the network is pre-trained for 40 epochs. After the pre-training, two networks are derived from the root network by adding or subtracting Gaussian random noise as described in Section III.A. Then the data clustering-driven training is applied. During the recursive training, since networks have been trained before, each iteration requires less epoch. Therefore, the learning rate is set to 0.01-0.0001. In our experiment, each network is trained using the partitioned datasets with exponentially decaying learning rates for 30 epochs. After several iterations, the training loss will converge and the derived networks’ parameters will stabilize (e.g. clustering centers no longer move). After the recursive training, if more DCDNN modes are needed, each network can be split into two networks, and then the data clustering-driven training is applied again. The learning rates for training DCDNN are listed in Table I.

| Num of Epochs | Decay Method   | Learning Rate  | Step |
|---------------|----------------|----------------|------|
| Pre-train     | 40             | Exponentially  | 0.1-0.0001 | 10   |
| Recursive     | 30             | Exponentially  | 0.01-0.0001 | 10   |

In DCDNN, specific networks are designed for two chroma components individually. The number of chroma networks is equal to the number of luma networks. Only one round of training is performed for chroma networks, and the learning rate is the same as that of the luma networks during the pre-training.

**D. Integrating DCDNN in HEVC**

To test the performance of DCDNN, we embed DCDNN into HEVC reference software. In HEVC, the coding mode (e.g. intra or inter) is decided at the CU level, and the best prediction mode is decided at the PU level. In our implementation, the encoder performs rate-distortion optimization (RDO)
to choose the better coding mode between DCDNN and HEVC intra prediction at the CU level. A new flag has to be coded and transmitted in the bitstream to indicate whether DCDNN is utilized or not. If DCDNN is chosen, the best DCDNN mode will be selected at the PU level. \( \text{Log}_2(\mathcal{K}) \) (\( \mathcal{K} \) is the number of DCDNN modes) bits are used to represent the best DCDNN mode. Consequently, the Context-Based Adaptive Binary Arithmetic Coding (CABAC) \([37]\) is used as the entropy coder. A context model is defined for the new flag coded at the CU level. The \text{Initvalue} of the newly defined context models is set as 154. Another context model with the same \text{Initvalue} is also defined for coding the DCDNN mode.

Fig. 6 shows an example of integrating DCDNN into the HEVC framework.

In DCDNN, the chroma components use the same DCDNN mode as the luma component, thus no additional flag is needed for coding the DCDNN modes of the chroma components. As four kinds of luma block sizes and three kinds of chroma block sizes are supported in HEVC, the number of integrated networks is \( 10 \times \mathcal{K} \).

### IV. Experiment Results

In this section, the experiment results of DCDNN are presented and analyzed in detail. Firstly, we introduce the experiment setting briefly. Then the network training is elaborated in detail. After that, the overall performance of DCDNN and the complexity are presented. Finally, some visual results and more analyses are provided.

#### A. Experiment Setting

To test the performance of DCDNN, it is implemented into HEVC reference software HM-16.9 \([25]\). All experiments comply with the common test conditions specified in \([38]\) with QP set as 22, 27, 32, and 37, and the all-intra main configuration is deployed. The HEVC common test sequences, which include 18 video sequences with different resolutions, grouped as \text{ClassA}, \text{B}, \text{C}, \text{D}, \text{E}, are utilized for experiments, and the first frame of each sequence is tested. All quantization parameters (QPs) share the same DCDNN models. BD-rate \([29]\) is used to evaluate the bitrate saving performance.

#### B. Network Training

The training data is generated from 800 pictures randomly picked from \( \text{DIV2K} \) image set \([39]\). These images are converted to YUV 4:2:0 colour format and then resampled to 5 resolutions (2560×1600, 1920×1080, 832×480, 416×240, and 1280×720) in HEVC video sequences. All training images are encoded by HEVC reference software HM-16.9 with all intra configuration. The QP is set to 22, 27, 32, and 37. After the encoding, the compressed bitstream is obtained and the reconstructed reference samples can be extracted from the bitstream on the decoder side as the network input. The original pixels are obtained from the uncoded images and taken as the network output.

It should be noted that, before the recursive training, all training data should be pre-processed by zero-centering to get rid of the low-frequency component and make the training easier. Specifically, the mean of the network input (i.e. surrounding reference samples) should be subtracted from both the network input and the original block pixels. In \([8]\) and \([11]\), blocks with complex textures are excluded from the network training dataset since such data would degrade network training efficiency and practical performance. The mean square error (MSE) between the original block pixels and the predicted pixels is exploited to measure the block complexity, and a threshold is set as \( 2 \times \text{MSE} \) where \( \text{MSE} \) represents the prediction error of each entire picture. Only blocks whose MSEs are smaller than the threshold are kept for training. We also adopt this strategy in our training.

In our experiments, DCDNN is trained using the DL framework Caffe \([40]\) on Intel Core i7-4790 CPU. All models are trained with a batch-mode method and the batch size is set as 128 for small blocks (4×4 and 8×8) and 64 for large blocks (16×16 and 32×32).

#### C. Overall Performance

In the experiment, the number of derived modes of DCDNN is set to a power of two for easy network split, e.g. two, four, and eight modes are derived to test the compression performance of DCDNN, represented by DCDNN-2, DCDNN-4, and DCDNN-8, respectively. The experimental results are shown in Table \( \text{III} \). As observed, DCDNN can bring bitrate saving of 4.2%, 3.5%, and 2.9% for the luma component when eight, four, and two modes are implemented, respectively. When DCDNN-8 is employed, the BD-rate improvement on 4K sequences (i.e. \text{ClassA}) reaches 6.5%. As the number of DCDNN modes increases, the BD-rates of two chroma components decrease slightly.

The Bjøntegaard delta PSNR (BD-PSNR) \([29]\) of the luma component is calculated to evaluate the prediction capacity of DCDNN. The results are shown in Table \( \text{III} \). As shown in Table \( \text{III} \), the BD-PSNR is improved after applying DCDNN. The BD-PSNR for the luma component is roughly 0.235, 0.193, and 0.161 dB on average (up to 0.417, 0.360, and 0.308 dB) for DCDNN-8, DCDNN-4, and DCDNN-2, respectively.

In addition, the generalization ability of DCDNN under different QP settings is also evaluated. We set the large QPs as \{33, 38, 43, 48\} and small QPs as \{11, 16, 21, 26\}. The
TABLE II
THE BD-RATE RESULTS OF DCDNN

| Sequences          | Traffic          | PeopleOnStreet | DCDNN-8 | DCDNN-4 | DCDNN-2 |
|--------------------|------------------|----------------|---------|---------|---------|
| Class A (4k)       | -6.0% -2.0% -1.7% | -5.0% -2.1% -2.0% | -4.3% -2.2% -2.1% |
| Class B (1080p)    | -2.2% -1.2% -0.7% | -1.7% -1.8% -0.4% | -1.6% -1.1% -0.2% |
| Class C (WQVGA)    | -4.8% -0.7% -1.0% | -4.4% -0.6% -1.3% | -3.7% -1.8% -2.4% |
| Class D (WQVGA)    | -2.9% 2.4% 1.2%  | -2.4% 0.2% 0.1%  | -2.2% 0.3% -0.5%  |
| Class E (720P)     | -3.8% -0.2% -0.1% | -3.0% 0.2% 0.1%  | -2.5% -0.4% -0.0%  |

TABLE III
THE BD-PSNR OF DCDNN COMPARED WITH HM-16.9

| Sequence          | BD-PSNR(dB) | DCDNN-8 | DCDNN-4 | DCDNN-2 |
|-------------------|-------------|---------|---------|---------|
| Class A (4k)      |              | 0.335   | 0.360   | 0.308   |
| Class B (1080p)   |              | 0.080   | 0.061   | 0.057   |
| Class C (WQVGA)   |              | 0.210   | 0.193   | 0.160   |
| Class D (WQVGA)   |              | 0.074   | 0.061   | 0.058   |
| Class E (720P)    |              | 0.122   | 0.107   | 0.084   |

TABLE IV
THE BD-RATE OF DCDNN UNDER LARGE QPS

| Sequence          | DCDNN-8 | DCDNN-4 | DCDNN-2 |
|-------------------|---------|---------|---------|
| Class A (4k)      | -7.3%   | -6.3%   | -5.4%   |
| Class B (1080p)   | -4.2%   | -3.7%   | -3.2%   |
| Class C (WQVGA)   | -4.1%   | -3.8%   | -2.8%   |
| Class D (WQVGA)   | -3.7%   | -3.3%   | -2.5%   |
| Class E (720P)    | -5.3%   | -4.3%   | -3.9%   |
| Overall           | -4.8%   | -4.2%   | -3.6%   |

TABLE V
THE BD-RATE OF DCDNN UNDER SMALL QPS

| Sequence          | DCDNN-8 | DCDNN-4 | DCDNN-2 |
|-------------------|---------|---------|---------|
| Class A (4k)      | -3.9%   | -3.2%   | -2.5%   |
| Class B (1080p)   | -2.7%   | -2.2%   | -1.7%   |
| Class C (WQVGA)   | -2.1%   | -1.5%   | -1.1%   |
| Class D (WQVGA)   | -1.6%   | -1.1%   | -0.8%   |
| Class E (720P)    | -3.1%   | -2.7%   | -2.1%   |
| Overall           | -2.7%   | -2.1%   | -1.6%   |

BD-rates are shown in Table II and Table IV. According to the tables, DCDNN can improve coding efficiency under different QP configurations. If DCDNN-8 is employed, the bitrate saving of 4.8% and 2.7% can be achieved under large and small QP settings, respectively. The results reflect that DCDNN has good generalization ability and brings remarkable bitrate saving under large range QP settings. As explained in [8], since the network modes are much fewer than HEVC intra modes, the network-based prediction strategy can save overhead greatly compared with HEVC intra prediction. Under the large QP setting (i.e., low bitrate), the encoder is more sensitive to overhead. Therefore, DCDNN can achieve better bitrate saving under a larger QP setting.

To show the efficiency of DCDNN, we calculate the usage rate of DCDNN at the pixel level. The statistical formula is defined as:

$$\eta = \frac{\sum (n \times N^2)}{W \times H}, \quad N \in \{4, 8, 16, 32\},$$  \hspace{1cm} (4)$$

where $\eta$ denotes the usage rate, $W$ and $H$ denote the width and height of each frame. $n_N$ represents the number of TUs with a size of $N \times N$ coded by DCDNN in each frame. The usage rate of DCDNN in each class is the average usage rate of all test sequences in that class. The QPs are set as $\{22, 27, 32, 37\}$. As shown in Table VI, the average usage rate of DCDNN in all test sequences is 57.4%, 53.3%, and 46.4% (up to 67.2%, 63.1%, and 55.9%) when DCDNN-8, DCDNN-4, and DCDNN-2 are implemented, respectively, which demonstrates the efficiency of DCDNN.
In this paper, considering the complexity, we only test DCDNN which contains two, four, or eight network modes. If the number of DCDNN modes is reasonably increased, better experimental results can be expected.

D. Complexity

In DCDNN, the dimension of the network is 128, 256, 256, 512 for blocks of size 4×4, 8×8, 16×16, and 32×32, respectively, while in IPFCN, the dimensions of networks are set to be 512, 1024, 1024, and 2048 to pursue the best prediction performance.

The encoding time, the decoding time, and the BD-rate of DCDNN and IPFCN are shown in Table VII. The test for DCDNN is done with Intel Core i7-4790 CPU and the test for IPFCN is done with Intel Xeon E7-4870 CPU. As observed, compared with IPFCN-D, DCDNN shortens the encoding time and decoding time remarkably even though more networks are integrated. Moreover, DCDNN could improve BD-rate performance more significantly than IPFCN-D and IPFCN-S.

In addition to the running time, the increase of implementation complexity is also analyzed. Firstly, 256 bits are allocated in the memory to store the network mode usage flag at the CU level. Another 2 × (32 + 32 + 8) × (32 + 32 + 8) ÷ (1024) = 10.125KB (short type) are allocated in the memory to store the 8-line reference samples since the maximum TU width is restricted to 32 in HM 16.9. If considering the parallel processing at the CTU level, the additional memory cost will be increased by several times. Secondly, storing the integrated Caffe model and deployment files will cost some memory. The size of files and models are listed in the Table VIII. The memory costs for storing networks’ parameters are calculated according to the architectures (the data type of weight is float).

E. Some Visual Results and More Analyses

To show the experiment results visually, We take the first frame of FourPeople encoded with QP=27 as an example. The distribution of PUs coded by DCDNN-4 is shown in Fig. 8. As shown in Fig. 8, regions with complex textural patterns are more likely to choose DCDNN rather than HEVC intra modes. The foreground parts of the picture, for example the human details, are mostly coded by DCDNN. Instead, the background parts, which have smooth textures or clear direction trends, prefer HEVC intra prediction modes.

Fig. 9 shows some examples of prediction results of DCDNN-4 and HEVC, taken from the same picture. As observed, DCDNN could produce more accurate predictions than HEVC when dealing with complex blocks. For instance, the original texture in Fig. 9(c) has an obvious gradient trend inside the block. In Fig. 9(d), the block texture is complex and no obvious directional pattern can be observed. Compared with HEVC intra prediction which only generates simple directional textures, DCDNN generates the predictions that are closer to the original textures, and the prediction errors (MSE) in Fig. 9(c) and Fig. 9(d) are reduced from 390.3 to 5.6 and from 383.6 to 17.9, respectively.

In addition, the usage rate of each DCDNN mode in the same picture is provided in Fig. 7. The usage rates of DCDNN in PUs of different sizes are calculated separately. Since the amount of 64×64 TU is quite small, blocks of such size are not included in the usage statistic. As shown in Fig. 7, each derived DCDNN mode is critical for intra prediction.

To show how DCDNN substitutes HEVC intra prediction modes, the usage of HEVC directional prediction modes w or w/o DCDNN is calculated when testing on the same picture. As shown in Fig. 10, if DCDNN is integrated, more than half of HEVC intra modes, especially DC mode, planar mode, the horizontal mode, and the vertical mode, are substituted by DCDNN.
Fig. 8. The distribution of PUs coded by DCDNN-4. Green, yellow, blue and red squares represent DCDNN mode 1 to 4, respectively. The parts not enclosed by squares are encoded by HEVC intra modes.

Fig. 9. Some examples of prediction results of DCDNN-4 and HEVC. The block size is $4 \times 4$. The reference information contains 8 lines of reference samples. For each example, the origin block is labeled with an orange square and the best DCDNN mode is labeled with a red square.
To assess the quality of the clustering and show the benefit of DCDNN, we give some investigations on the prediction losses from the network split and data clustering-driven training. The training losses for DCDNN-2 and DCDNN-4 are shown in Fig. 11 and Tables IX-X. After dividing two network modes into four, the derived networks (DCDNN-4) have stronger predictive ability (lower training loss) than the parent networks (DCDNN-2). As shown in Tables IX and X, even if DCDNN-4 is only trained once, the average prediction loss of each network mode in DCDNN-4 is much smaller than that in DCDNN-2, which shows that the network splitting from two to four is beneficial for prediction.

The quality of data after each round of data clustering can also be measured by the prediction losses of networks. We analyze the prediction loss of each network mode in DCDNN-2 and DCDNN-4 in each round of data clustering. As shown in Tables IX and X, for each DCDNN mode, the average prediction losses gradually decrease and converge with the data clustering-driven training going on. From Fig. 11 the training loss curve continues going down after each round of data clustering. This indicates that the data clustering-driven training strategy could help enhance networks’ prediction ability.

In each round of data clustering, the entire training dataset is partitioned according to the recovery qualities of the derived networks. After one round of data clustering, some data may remain in the same cluster, while others may move to other clusters. We conduct a statistic about the rate of samples remaining in the same cluster after each round of data clustering on DCDNN-4 to see whether the recursive training could finally converge. As shown in Table XI, less and less data is clustered to other clusters with the increase of clustering rounds, which indicates that the clustering is gradually stabilizing.

V. CONCLUSIONS

A novel data clustering-driven neural network for intra prediction is proposed in this paper. In DCDNN, each network can be split into two networks by adding or subtracting Gaussian random noise. Then a data clustering-driven training is applied to train all the derived networks recursively. This strategy could enable networks to learn deep patterns that are not necessary directional and generate more reasonable prediction results. In addition, the number of network modes in DCDNN could be controlled flexibly by observing the training loss before and after each split to decide if the split is beneficial for prediction. The improvement in networks’ prediction capability could help ameliorate coding efficiency.

Although DCDNN is implemented into HEVC in our experiment, it can also be applied to other hybrid video coding frameworks, such as the recently released H.266/VVC. In the future, the split strategy will be investigated, so that more detailed and complex image patterns can be learned and handled better. Meanwhile, we will also try to accelerate the proposed method, for example by simplifying the network architecture and making rapid mode decision, to make it more practical for industrial usage.

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