Efficient Adaptation of Neural Network Filter for Video Compression

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ABSTRACT
We present an efficient finetuning methodology for neural-network filters which are applied as a postprocessing artifact-removal step in video coding pipelines. The fine-tuning is performed at encoder side to adapt the neural network to the specific content that is being encoded. In order to maximize the PSNR gain and minimize the bitrate overhead, we propose to finetune only the convolutional layers’ biases. The proposed method achieves convergence much faster than conventional finetuning approaches, making it suitable for practical applications. The weight-update can be included into the video bitstream generated by the existing video codecs. We show that our method achieves up to 9.7% average BD-rate gain when compared to the state-of-art Versatile Video Coding (VVC) standard codec on 7 test sequences.

CCS CONCEPTS
• Computing methodologies → Neural networks.

KEYWORDS
Neural Networks; Video Coding; Adaptive Filter; Efficient Adaptation

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1 INTRODUCTION
Digital video content is accounted for the majority of media transmission nowadays. Due to its richness in content, the high volume demand poses challenges to bandwidth utilization, thus making video compression an essential technology. However, compression algorithms often generate artifacts in the decoded video which reduce the visual quality perceived by observers.

These compression artifacts are similar in many different compressed video contents so it is possible to suppress them by filtering. Apart from the traditional filtering approaches, convolutional neural networks (CNNs) were integrated into the traditional codec to replace the traditional filters [8]. CNNs can be also used as a post-processing filter after the traditional decoding steps [3, 5]. As for neural network architectures, several works have adapted architectures which were initially thought for super-resolution tasks, and used them for reducing compression artifacts [18].

While other works [17, 19] utilize multiple networks to allow some adaptability to the content, we present a novel approach in this paper to send bias only weight-update as adaptation signal to achieve the adaptation in a much more efficient way. A basic post-processing filter is pretrained on a general image dataset to learn the general types of compression artifacts. The pretrained filter is incorporated in the decoder side after the traditional decoding steps. In encoding stage, the filter is adapted on the target video content by finetuning only the bias terms of the convolutional layers. The updated coefficients of the bias terms are then encoded and provided to the decoder.

2 RELATED WORKS
2.1 Artifact Removal Filtering in Video Coding
In the conventional video compression standards, various types of compression artifacts (e.g., blocking, ringing, contouring effects, and blurring) appear due to the block-based coding and quantization structure. The artifact removal filters can be designed either as out-of-loop/post-processing filtering (i.e., performing at the decoder end) or in-loop filtering (i.e., performing at both encoding and decoding loops). In the upcoming video coding standard, Versatile Video Coding (VVC) [7], three in-loop filters namely de-blocking filter (DBF), sample adaptive offset (SAO), and adaptive loop filter (ALF), have been designed. The filters are applied sequentially in a pre-defined order as DBF, SAO and ALF. The recent studies demonstrated great success in applying CNN-based methods to outperform the conventional filters in suppressing compression artifacts.
artifacts. CNN-based methods were proposed to replace the conventional filters [8, 16] or integrated to be used along with the traditional filtering chain [12].

2.2 Transfer Learning of Filter
In ALF in-loop filter [4], in order to improve the adaptive capacity of the filter, the filter coefficients are trained at the encoder side and transmitted to the decoder. Similarly, in CNN-based methods finetuning process allows a neural network to adapt to the context by updating existing weightings with new training data. One common technique used when finetuning part of a neural network is layer freezing, which allows to update only part of the weights and keep other weights unchanged. It is commonly used for example in transfer learning to retain the knowledge from the original network. In some popular computer vision tasks, such as classifiers or object detectors [6], the initial layers of the network are kept unchanged and only the last layers are finetuned to adapt to the new task. Instead of transferring the knowledge to a new domain or a new task, we want to finetune the pretrained knowledge of image enhancement to the target content which is in the same domain and for the same task. The adaptation does not require a topological change of the network but finetuning in weighting values. In our research, we demonstrate that this finefuning can be done more efficiently through bias-only updating and freezing the other weights of convolution layers.

2.3 Neural Network Representation of Filter
In [15], the authors propose a method for jointly finetuning and compressing a pretrained neural network to adapt the network to a more specialized domain than the pretraining domain, in order to avoid overfitting due to over-parameterization. However they have to send the whole neural network which is too costly in our application. In [10], the authors suggest an efficient way to reduce the size of adaptation signal of postprocessing filter for image compression. The finetuning of postprocessing neural network is conducted with compressive training. However, that work focuses on image compression and there is no consideration on bandwidth limitation which is crucial for video compression and is a much more time-consuming process, as it considers all the weights and adds one more training loss term. In our approach, we aim to send adaptation signal in an even more efficient way, by treating the weights of a layer and its bias terms differently.

3 METHODOLOGY
The outstanding performance in suppressing compression artifact of CNN-based filters depends on its numerous hidden layers and neurons, which means a huge amount of parameters. The single-network based methods have a limited adaptation capacity and require high bitrate to extend their adaptation power, because of the high number of parameters to update. In this work, an efficient and highly adaptive filtering approach is proposed which is based on computing an adapted network for each adaptation interval. In the encoder, the adapted network is computed by performing a finetuning process using a pretrained network which has a general knowledge about different types of artifacts. Then a light weight update signal is generated and transmitted to the decoder side by comparing the adapted and pre-trained networks. The update signal is limited to bias-only parameters to reduce the signalling overhead, while preserving a great deal of adaptation potential. In the decoder side, the adapted network is reconstructed using the update signal and the exact pretrained network embedded in the decoder.

3.1 Overview
The proposed method consists of using a traditional codec empowered by a post-processing neural network filter. The overall pipeline is shown in Fig. 1. The traditional components include encoder and decoder with the in-loop filters enabled, which are shown in yellow blocks. A pretrained neural filter is obtained by offline training on a large dataset. The pretrained filter is included in both encoder and decoder. On encoder side, the pretrained filter is finetuned with the target video sequences. The finetuned network can be represented by the weight-update which is transferred with the encoded bitstream. On the decoder side, the adapted filter is restored by the built-in pretrained filter and weight-update. Finally the adapted network is applied on the decoded frames at the decoder end as an out-of-loop filter.

3.2 Weight-update as Adaptation Signal
A traditional way of network adaptation is to clone the pre-trained network and continue training the network on the specific domain. However this process involves retraining of large amount of parameters, which is a computational expensive process. Furthermore, as the amount of parameters grows with the depth and the number of filters in CNN networks, this naÃўve approach is not feasible with large networks, as the weight-update to be encoded would
be prohibitively large. In [10], an updated neural network can be represented as an addition of a pretrained approximation neural network and an updating signal representing the adaptation. In such manner, only the difference between the pretrained network and finetuned network, which is significantly smaller in storage size, is used for the update. Our approach is inspired by them to represent the finetuned network with weight-update.

By sacrificing the adaptive power of neural network, the size of weight-update can be further reduced by imposing constraints on the finetuning process. The finetuning process of [10] is carried out with a compressive loss. It attempted to reduce the size of adaptation signal with compressive training that avoids unnecessary change in neural network. However, the introduced subsequent quantization process brings extra computational burden. Furthermore, the bit rate of the resulted weight update signal is high for video coding application as the weight-update signal involves a lot of parameters from two-dimensional convolutional layers.

Our breakthrough lies on the bias-only adaptation on top of a well pretrained neural network. Our hypothesis is that the noise-removal knowledge is stored in the local structure of two-dimensional convolution kernel, which should keep unchanged in the finetuning process. Only bias in the neural network should be updated in the finetuning process. Even under this restriction, significant visual quality improvement can be obtained. Compared with [10], it is a straightforward approach to constrain the finetuning scope. It involves much less parameters being trained compared to updating the whole neural network (Table 1). Consequently, the computational load and signalling overhead are significantly reduced and the neural network converges faster.

### 3.3 Pretraining Stage

From the prospective of machine learning, the pretrained neural network should be a good approximation of the finetuned network in order to minimize the size of adaptation signal. In our application the approximation is possible due to the similarity of compression artifact of a specific traditional codec. We desire a pretrained network to have a good generalized knowledge on the specific codec behaviour.

The pretraining stage aims to train a post-processing filter that is embedded in the traditional codec on both encoder and decoder sides. In our methodology, the pretraining stage is particularly important as the pretrained two-dimensional kernel will be used directly at the decode end. The pre-trained neural network should be trained on a large and diverse content. Ideally, the training data should cover different variety of content in different intended applications. Different compression artifacts generated by a codec can be created by encoding and decoding the training data. The original and decoded version of the data are used pairwise for network training. The codec setting should be identical to the intended application so the the compression artifacts are similar to those in application case. The training optimizes quality of processed data which is evaluated by a quality index. The implementation of pretraining, including the traditional codec, dataset and training parameters will be discussed in 4.1.

### 3.4 Finetuning Stage and Representation of Weight-update

In the finetuning stage, we want to specialize our neural network to improve the visual quality of a target video sequence. According to our hypothesis, the weights of convolutional kernels learned on a general image database should also work on the test video set, therefore it is unnecessary to retrain them. The only changes which are required in order to adapt the pre-trained model to the target video is the bias terms of the model.

The finetuning process takes place online, after traditional encoding process which matches with the one in pre-training process. In a similar manner as in the pretraining stage, the pairwise original and content are used to finetune the pre-trained neural network. The only exception is that the weights of the convolutional kernels are frozen except for the bias terms, which are finetuned. The obtained weight-update is then compressed and included into the bitstream.

At decoder side, the adapted neural network is updated by replacing the bias term of the embedded pretrained network with the decompressed weight update signal. The adapted filter is applied on the decoded content for removing the compression artifacts. The bias terms of the pretrained network are updated based on an adaptation interval which is configurable.

### 4 EXPERIMENTS

To prove our hypothesis in Section 3, the methodology is implemented on a video compression task and evaluated on different video sequences from the Joint Video Exploration Team (JVET) common test conditions and evaluation procedures [11] to improve the performance of a traditional video codec. The implementation and evaluation details are discussed in the following subsections.

#### 4.1 Implementation Details

The methodology is based on the adaptive training of a post-processing filter. The aim of the filter is to improve the visual quality of decompressed video sequence, which is evaluated by the difference between decompressed frames and their corresponding source frames in terms of peak signal-to-noise ratio (PSNR). However, it is also preferable to minimize the size of weight-update which is transmitted to the decoder. Thus, the goal of the task is to decrease the BD rate in Bjontegaard metrics of rate-distortion-curves (RD-curve) [2] which reflects a better trade-off between the bitrate and distortion.

### Table 1: Distribution of parameters in the neural networks with different number of filters \(N_{\text{filters}}\) and number of blocks \(N_{\text{blocks}}\)

| Network Structure \(N_{\text{filters}} \times N_{\text{blocks}}\) | No. of parameters | Bias | Total | Bias/Total % |
|-------------------------------------------------|-----------------|------|-------|--------------|
| 512 \times 5                                    | 7109652         | 256  | 7112195| 0.036        |
| 512 \times 4                                    | 4750336         | 2051 | 4752387| 0.043        |
| 256 \times 6                                    | 2965248         | 1539 | 2966000| 0.052        |
| 256 \times 5                                    | 2375424         | 1283 | 2376707| 0.054        |
| 128 \times 7                                    | 746115          | 771  | 745886  | 0.103        |
| 128 \times 6                                    | 598531          | 643  | 598531  | 0.107        |
| 64 \times 7                                     | 188739          | 387  | 188152  | 0.205        |
| 64 \times 6                                     | 151811          | 323  | 151488  | 0.213        |
Test Model VTM-7.0. The test model takes an uncompressed raw video frames. The input consists of four channels: the Y channel of video or image as input. The test video clips are in YUV 4:2:0 color video codecs are available, the traditional video codec used in our JVET common test conditions (CTC). In order to allow the neural network to perform well during testing phase, the encoding and decoding settings should be similar when encoding/decoding the input. The output of the neural network network consists of three channels representing the YUV channels.

The neural network is formed by blocks consisting of a layer that includes the convolutional kernel’s weights (excluding the bias terms), a layer that includes only the bias terms, and an activation layer of type leaky rectified linear unit (LeakyReLU). The number of convolutional filters, \( N_{\text{filters}} \), is same for all blocks. The convolutions are applied with stride 1, so the size of the output at each block is same as the size of its input. The kernel size of the convolutional layers is \((3, 3)\). There are skip connections (solid blue arrows) between the input of the blocks and the output of the blocks. There is another global skip connection (dashed blue arrow) from the input to the output of the whole network. The output consists of three channels of same resolution, i.e., the Y, U and V channels. In general, the trainable parameters in the neural network are those from the convolutional kernels and from the bias layers. In the pretraining stage, all the parameters are trained. In the finetuning stage, only the parameters in bias layers are trained.

The post-processing filter is trained to remove the artifacts and restore the frame with better visual quality. We aim to optimize the peak signal-to-noise ratio (PSNR) of the filtered frames, thus the mean squared error (MSE) between filtered patches and original patches is used as the training loss. PSNR is used as the evaluation metric, which is commonly used in video compression, for example as one of the reported metrics in JVET common testing condition. PSNR is also used in BD-rate calculation which is the metric we desired to optimize in our task.

4.1.3 Pretraining Stage. For the pretraining stage, the 1633 images in Portable Network Graphic (PNG) format from the training dataset of the Competition on Learned Image Compression 2020 (CLIC) [1] is used as input. The dataset provides images of various contents and scenes, which is good for training an initial version of the filter. The images are first encoded by the VVC/H.266 test model using All Intra (AI) configuration. The corresponding decoded images and original images are used as training samples (input-target pairs) of the neural network model.

The neural network post-processing filter is pretrained offline. Patches of size \((128, 128)\) are cropped randomly over VVC decoded images. These patches are used as training input to the neural network, whereas the corresponding patches obtained from the original uncompressed images are used as the ground-truth. During training, each batch contains 64 patches from 64 different random
images in the dataset. At every training epoch, 32768 patches (in 512 batches) are used. The pretraining process is a long process that takes 2000 epochs, but the total training time depends on the size of the neural network. The learning rate is controlled by the Adam optimizer [9], with initial learning rate of 0.001.

4.1.4 Finetuning Stage. In the finetuning stage, the 7 different video sequences defined in the Joint Video Exploration Team (JVET) common test conditions and evaluation procedures [11] are used. The sequences are encoded using Random Access (RA) configuration with the first 49 frames for each sequence. The frames are broken down into patches of (128, 128) before the finetuning process. The patch size of (128, 128) is chosen as the largest available size in a coding tree unit (CTU) defined in the VVC codec. The decoding refresh type was set to instantaneous decoding refresh (IDR) picture with a period of 16. The sequences have resolution of either 832x480 or 1920x1080, thus belonging to group C of group B video sequences of JVET dataset, respectively.

The finetuning process is similar to the pretraining process except that only bias terms are updated. In each epoch, all patches (decoded-original pair) are used in the finetuning. The learning rate is also controlled by Adam optimizer but it was decayed to half of its value every 20 epochs until epoch 110. This decay showed to be successful empirically, in terms of better training performance and faster convergence.

4.1.5 Packaging and Decoding Stage. The resultant bias terms are flattened to a one-dimensional array of 64 bits floating point numbers and further packaged with 7z, which is a popular lossless compression method based on LZMA2 [13, 14]. The compressed package is subsequently decompressed in the decoder side. The original bias terms in the pretrained network are replaced with the updated ones from the signaling, while the convolution layer terms remained unchanged. The updated neural network is used to filter the VTM-decoded patches.

4.2 Results

4.2.1 Overview. In Table 2, the performance of the proposed method is compared against that of the conventional VVC-based coding method. The result of the pretrained filters without adaptation are also shown for comparison. The results are reported in terms of Bjontegaard Delta-rate (BD-rate) criterion [2] for luminance (Y), chroma components (U and V), and a weighted average over the three channels (YUV). For combined YUV BD-rate, in order to compute YUV-SNR, a weighting of (6, 1, and 1) is used for Y, U, and V channels, respectively. In case of VVC, the bitrate and PSNR values reported by VTM are used to compute BD-rate. To report the performance of the proposed method, the bitrate of finetuned network is computed by adding the weight-update signaling overhead to the bitstream size achieved from VTM, and PSNR is calculated between the content processed by the finetuned neural network model and the uncompressed source content. The pretrained network is considered part of the codec so there is no extra overhead caused by the pretrained filter.

As can be seen from the table, apart from some cases with more complex architectures (i.e., using more blocks and convolutional filters), usually a pretrained filter cannot provide any improvement on BD-rate. Although a general pretrained filter does not incur any extra overhead, it cannot effectively improve the BD-rate performance. After adaptation, all filters can improve the BD-rate on all the video sequences. For high resolution group B video sequence, the more complicated the network (with higher \(N_{\text{blocks}}\) and \(N_{\text{filters}}\)), the better improvement in BD-rate. This trend can also be observed in the performance of pretrained filter. It reflects that a complex filter can show better noise-removing ability than a simpler one. The best performance is obtained with a postprocessing filter with \(N_{\text{blocks}} = 5\) and \(N_{\text{filters}} = 512\) on BVQTerrace dataset which brings up to 9.7%, 6.8%, 17.1% and 20.2% gain in BD-rate over combined YUV, Y, U, and V channels, respectively. The performance also depends on the video sequence itself, varying from 4.4% to 9.7%. There are also significant differences between luminance channel and chroma channel: the BD-rate gain of chroma channel can be up to 20%, while that of luminance is up to 6.8%.

For lower resolution video, the effect of the extra finetuning overhead is more significant so it is preferable to use architectures which introduce a smaller overhead. Usually a smaller filter (for example \(N_{\text{filters}} = 128\)) gets a similar result as the larger one due to the smaller overhead. In some situations (C_BQMall and C_BasketBallDrill), a complex pretrained network can outperform the finetuning methodology in BD-rate as pretraining-only approach does not introduce any overhead.

4.2.2 Analysis. A detailed analysis (Table 3) is done on the first 49 frames of two video sequences B_BQTerrace and C_PartyScene with two different neural networks \((N_{\text{blocks}} = 7, N_{\text{filters}} = 128\) and \(N_{\text{blocks}} = 5, N_{\text{filters}} = 512\)) on two different video sequences C_PartyScene (CPS) and B_BQTerrace (BCT).

![Figure 3: BD-rate-epoch plot of different video sequences with the two neural networks \((N_{\text{blocks}} = 7, N_{\text{filters}} = 128\) and \(N_{\text{blocks}} = 5, N_{\text{filters}} = 512\) on two different video sequences C_PartyScene (CPS) and B_BQTerrace (BCT).](image)
Table 2: BD-Rate of filtered patches compared to the VTM decoded patches. A negative BD-rate indicates an improvement of quality and the best configurations of each dataset are highlighted in bold letters. The network is labelled as $N_{filters}$.$N_{blocks}$

| Dataset         | Network | Pretrained BD-rate | Finetuned BD-rate |
|-----------------|---------|--------------------|-------------------|
|                 |         | YUV                | Y                | U       | V                  |
|                 |         |                    |                  |         |                    |
| **B_BasketBall**| 512_5   | -2.00              | -1.25            | -2.27   | -6.20              |
|                 | 512_4   | -1.46              | -0.93            | -1.75   | -4.36              |
|                 | 256_6   | -2.05              | -1.49            | -2.38   | -5.03              |
|                 | 256_5   | -1.90              | -1.30            | -2.37   | -5.03              |
|                 | 128_7   | 1.80               | 1.95             | 4.42    | -1.73              |
|                 | 128_6   | 1.51               | 1.18             | 7.65    | -2.71              |
|                 | 64_7    | 2.19               | 1.51             | 7.61    | 0.84               |
|                 | 64_6    | 1.66               | 1.66             | 3.67    | -0.36              |
| **B_BQTerrace**| 512_5   | -3.10              | -2.57            | -1.10   | -8.26              |
|                 | 512_4   | 1.35               | -0.35            | 10.22   | 2.69               |
|                 | 256_6   | -2.52              | -2.26            | 3.03    | -9.58              |
|                 | 256_5   | -3.18              | -2.66            | 0.91    | -10.41             |
|                 | 128_7   | 10.74              | 11.05            | 17.80   | 1.77               |
|                 | 128_6   | 12.05              | 10.93            | 19.30   | 11.48              |
|                 | 64_7    | 12.24              | 9.87             | 18.19   | 20.52              |
|                 | 64_6    | 8.22               | 8.57             | 16.97   | -2.61              |
| **B_Cactus**   | 512_5   | 1.19               | 0.04             | 3.51    | 5.78               |
|                 | 512_4   | 0.42               | 0.23             | -4.00   | 5.95               |
|                 | 256_6   | 1.09               | 0.66             | -1.92   | 6.64               |
|                 | 256_5   | 1.56               | 0.86             | -0.49   | 7.80               |
|                 | 128_7   | 8.60               | 6.17             | 4.18    | 27.59              |
|                 | 128_6   | 6.39               | 4.90             | 8.57    | 13.15              |
|                 | 64_7    | 9.20               | 5.62             | 7.48    | 4.71               |
|                 | 64_6    | 4.77               | 3.96             | 3.35    | 11.00              |
| **C_BasketBall**| 512_5   | -2.70              | -2.51            | -3.64   | -2.90              |
|                 | 512_4   | -2.15              | -2.02            | -1.57   | -3.54              |
|                 | 256_6   | -2.27              | -2.28            | -2.60   | -1.84              |
|                 | 256_5   | -2.06              | -2.02            | -1.76   | -2.60              |
|                 | 128_7   | 4.07               | 4.18             | 4.82    | 2.63               |
|                 | 128_6   | 3.39               | 2.06             | 7.59    | 7.22               |
|                 | 64_7    | 3.79               | 1.75             | 11.29   | 8.48               |
|                 | 64_6    | 3.09               | 1.65             | 7.14    | 7.65               |
| **C_BQMall**   | 512_5   | -4.29              | -3.55            | -6.91   | -6.17              |
|                 | 512_4   | -3.69              | -3.06            | -4.37   | -6.80              |
|                 | 256_6   | -3.63              | -3.37            | -4.62   | -4.19              |
|                 | 256_5   | -3.80              | -3.32            | -5.07   | -5.44              |
|                 | 128_7   | 0.41               | 1.04             | -0.88   | -2.11              |
|                 | 128_6   | 0.22               | 0.21             | 1.66    | -1.15              |
|                 | 64_7    | 0.95               | 0.17             | 3.53    | 3.04               |
|                 | 64_6    | 0.63               | 0.28             | 3.51    | -0.19              |
| **C_PartyScene**| 512_5   | -2.37              | -2.48            | -5.96   | 1.91               |
|                 | 512_4   | -1.99              | -2.02            | -5.97   | 2.19               |
|                 | 256_6   | -2.04              | -2.33            | -3.65   | 1.29               |
|                 | 256_5   | -2.09              | -2.31            | -3.66   | 0.79               |
|                 | 128_7   | 2.44               | 1.67             | 0.79    | 8.73               |
|                 | 128_6   | 2.71               | 1.06             | 5.88    | 9.39               |
|                 | 64_7    | 2.05               | 0.76             | 1.44    | 10.35              |
|                 | 64_6    | 1.67               | 1.07             | -0.17   | 7.08               |
| **C_RaceHorses**| 512_5   | -3.21              | -1.67            | -7.12   | -8.50              |
|                 | 512_4   | -2.58              | -1.39            | -5.92   | -6.38              |
|                 | 256_6   | -2.64              | -1.57            | -5.57   | -6.14              |
|                 | 256_5   | -2.52              | -1.55            | -5.49   | -5.36              |
|                 | 128_7   | -0.58              | 0.61             | -2.82   | -5.51              |
|                 | 128_6   | -0.58              | 0.31             | -2.59   | -3.88              |
|                 | 64_7    | 0.39               | 0.38             | 0.45    | 0.42               |
|                 | 64_6    | 0.10               | 0.31             | -0.56   | -0.48              |
Table 3: PSNR and the bitrate of the first 49 frames in two video sequences (B_BQTerrace and C_PartyScene). Anchor is the VTM 7.0 result and Test is the result after filtering with either 128_7 or 512_5 network. The % increase refers to the ratio between the absolute increase with the anchor bitrate.

| QP | Network | 22 | 27 | 32 | 37 |
|----|---------|----|----|----|----|
|    |         | 128_7 | 512_5 | 128_7 | 512_5 | 128_7 | 512_5 | 128_7 | 512_5 |
| Bitrate | Anchor | 36469 | 36469 | 7230 | 7230 | 2444 | 2444 | 1102 | 1102 |
| Test | 36502 | 36549 | 7262 | 7310 | 2477 | 2524 | 1135 | 1182 |
| Increase | 32.82 | 80.21 | 32.8 | 80.41 | 32.9 | 80.36 | 32.8 | 80.26 |
| % Increase | 0.09 | 0.22 | 0.45 | 1.11 | 1.35 | 3.29 | 2.98 | 7.28 |
| Average | Anchor | 39.15 | 39.15 | 36.96 | 36.96 | 35.42 | 35.42 | 33.68 | 33.68 |
| Test | 39.19 | 39.24 | 37.04 | 37.1 | 35.56 | 35.62 | 33.86 | 33.93 |
| Gain | 0.04 | 0.08 | 0.09 | 0.14 | 0.14 | 0.2 | 0.18 | 0.25 |
| Y-PSNR | Anchor | 37.95 | 37.95 | 35.62 | 35.62 | 34.07 | 34.07 | 32.3 | 32.3 |
| Test | 37.99 | 38.02 | 35.71 | 35.75 | 34.2 | 34.26 | 32.47 | 32.54 |
| Gain | 0.04 | 0.07 | 0.09 | 0.14 | 0.14 | 0.19 | 0.17 | 0.23 |
| U-PSNR | Anchor | 42.69 | 42.69 | 41.6 | 41.6 | 40.19 | 40.19 | 38.64 | 38.64 |
| Test | 42.7 | 42.82 | 41.61 | 41.8 | 40.31 | 40.5 | 38.89 | 39.12 |
| Gain | 0.01 | 0.13 | 0.02 | 0.2 | 0.12 | 0.31 | 0.25 | 0.48 |
| V-PSNR | Anchor | 44.77 | 44.77 | 43.67 | 43.67 | 42.34 | 42.34 | 40.91 | 40.91 |
| Test | 44.81 | 44.96 | 43.73 | 43.91 | 42.51 | 42.67 | 41.22 | 41.36 |
| Gain | 0.04 | 0.19 | 0.07 | 0.24 | 0.17 | 0.33 | 0.31 | 0.44 |

shown in Table 3. For bitrate, the results show that our proposed method introduces higher weight-update overhead percentage in lower bitrates (i.e., higher QPs). However, for these cases, also the PSNR gains are higher, as there are more significant artifacts in the input data. Furthermore, the results indicate that the improvement in PSNR decreases in higher bitrates where the task of removing compression artifacts becomes more challenging for the neural network model, as artifacts are less significant. Although only the result related to two sequences are presented in Table 3, a similar behavior is observed for the other tested video sequences.

4.2.3 Complexity. To study the complexity of our methodology, the whole pipeline is broken down into five steps. The time measurements are reported in Table 4. Pretraining time is the time required to train the filter from scratch with the pretrained dataset (CLIC dataset) on one single Nvidia Tesla V100 core. For fair comparison, both networks are trained for 1000 epochs. The pretraining time is very long, however the same network is used as the pretrained model for different test video sequences.
The VTM encoding process is done on a single CPU of Intel Xeon Gold 6154 without parallel processing. The processing time depends on the quality of video sequences, which includes the resolution and also QP.

Finetuning is performed on a single Nvidia Tesla V100 core for 110 epochs for each video sequence. The required time does not depend on the QP of the video but only on the number of processed patches, which grows with the resolution. While the required time seems to be long compared to VTM encoding time, the finetuning can be stopped earlier without a significant drop of the adapting performance. The required time for each epoch is nearly constant so the finetuning time can be reduced to ~9% of the reported time if the finetuning is stopped at 10 epochs. This can provide extra flexibility for different applications depending on the processing environment.

## 5 CONCLUSIONS

In this paper, we presented a new methodology to apply an adaptive post-processing filter for traditional video codecs. A pretrained neural network was trained offline on a generic image dataset. At encoding stage, we demonstrated the efficient adaptation of the neural network to the target video content by finetuning only the bias terms of the CNN. We evaluated the proposed idea on neural network was trained offline on a generic image dataset.

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