High-Efficiency Image Coding via Near-Optimal Filtering

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***Abstract*—Wiener filtering, which has been widely used in the field of image restoration, is statistically optimal in the sense of mean square error. The adaptive loop filter in video coding inherits the design of Wiener filters, and has been proved to achieve significant improvement on compression performance by reducing coding artifacts and providing high-quality references for subsequent frames. To further improve the compression performance via filtering technique, we explore the factors that may hinder the potential performance of Wiener-based filters, and propose a near-optimal filter learning scheme for high-efficiency image coding. Based on the analyses, we observe that the foremost factor affecting the performance of Wiener-based filters is the divergence of statistical characteristics of training samples, instead of the filter taps or shapes. In view of this, we propose an iterative training method to derive the near-optimal Wiener filter parameters by simultaneously labeling sample categories at the pixel level. These parameters are compressed and transmitted to the decoder side to improve the quality of decoded images by reducing the coding artifacts. Experimental results show that the proposed scheme achieves significant bitrate savings compared with high-efficiency video coding in high-bitrate intra coding scenario.**

***Index Terms*—High-efficiency video coding (HEVC), image compression, near-optimal filter, sample classification, wiener filter.**

I. Introduction

With the explosive increase of images/videos, compression technology [1]–[4] plays an important role in image/video communication and processing. The block-transform-based compression framework has been widely adopted for both images and videos, e.g., the popular image and video compression standards JPEG and High-efficiency video coding (HEVC). However, due to the quantization of transform coefficients, the compressed images usually suffer from visually annoying artifacts [5]–[7], including the blocking and ringing effects. Therefore, the filtering techniques have been widely investigated and applied to image/video coding problems to improve the quality of the decoded images by reducing the coding artifacts.

For image compression, there are numerous filtering algorithms proposed as postprocessing tools to reduce coding artifacts by utilizing image prior models [8]–[11]. Zhai *et al.* [8] utilized the average of multiple similar blocks to reduce compression artifacts. H.264/automatic volume control is the first video coding standard that adopts the filtering technique into the coding loop to reduce the blocking artifacts, and sophisticated *deblocking filter* (DF) [12] has been incorporated. In particular, multiple low-pass filters are well designed and applied to 4×4 block boundaries according to coding information of neighboring blocks, e.g., quantization parameters (QPs), intra/inter predictions and motion vectors. Moreover, the in-loop filtering performs better than postfiltering because it not only reduces the compression artifacts, but also provides high-quality references for subsequent video frames to achieve coding bitrate savings.

Besides DF, during the development of the latest video coding standard HEVC, another two filters sample adaptive offset (SAO) [13] and adaptive loop filter (ALF) [14], [15] have also been widely discussed. In fact, ALF and SAO both inherit the design of Wiener filters, and SAO only has one tap, whereas ALF has multiple taps. To derive the filter parameters, the reconstructed samples are first classified into different categories based on image statistical characteristics, and then the parameters are calculated by minimizing the distortions between the original and reconstructed samples in the same category. These parameters are further compressed and transmitted to the decoder side.

Although both SAO and ALF have achieved coding gain to some extent, the possible factors affecting their potential performance have not been well explored in the literatures. In [16], Lai *et al.* tried out filters with different taps and shapes in video coding, and showed 0.2% bitrate variations among different filters. In [17], Maani *et al.* investigated the sample classification based on sample gradients and activities, and the performance variations of ALFs are around 0.1% in bitrate. Since the filter taps and sample classification strategies in ALF have been sophisticatedly designed, straightforwardly modifying them may only lead to very limited coding performance improvement.

In this letter, we revisit the Wiener-based in-loop filtering technique and propose a near-optimal Wiener-based in-loop filtering method to further improve the image compression

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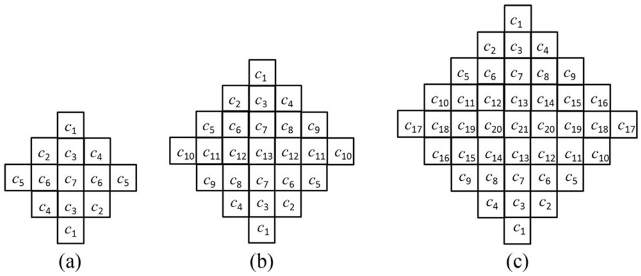


Fig. 1. Diamond-shaped filters with different filter taps. (a) 5×5; (b) 7×7; (c) 9×9.

performance. In particular, we find that the sample classification leaves us more room for the filtering performance enhancement, which inspires us to propose a novel and near-optimal in-loop filter training method. Afterwards*, we apply the near-optimal filters to the reconstructed images in image coding, and compress both the filter parameters and sample labels into the bitstream. Experimental results show that the proposed filtering scheme can achieve surprising restoration performance for an image with only four filters and, furthermore, improves the performance of HEVC in high-bitrate coding scenario.

The remainder of this letter is organized as follows. Section II first provides an in-depth analysis on the potential performance improvement room for the Wiener-based filters, and then introduces the proposed scheme in detail, including near-optimal filter training and sample classification learning. Experimental results are reported in Section III, and Section IV concludes the letter.

II. Proposed Near-Optimal Filters for Image Compression

A. Analysis of Wiener-Based Filters

In the traditional hybrid image/video coding framework, the filtering technique is utilized to improve compression performance by reducing the compression artifacts, e.g., DF [18], ALF [14], and SAO [13]. However, these methods mainly focus on how to design the filters with different taps and adaptively derive the parameters, e.g., Wiener filter, bilateral filter [19], and nonlocal similarity based filter [20]. In this letter, we focus on the Wiener-based filters, which are widely discussed in HEVC standard, and improve their performance by investigating the factors that affect their efficiency.

Based on previous research [21], [22], there are two possible factors that influence the performance of the Wiener-based filters, *i.e.*, filter taps and sample labels. To further explore them, we employ the three symmetric diamond-shaped filters with different taps as in Fig. 1 and the gradient-based sample classification method [14] to analyze the filtering performance. Here, we train four Wiener filters for an image.

For convenience of the later discussion, we denote the original and the decoded images as $\boldsymbol{x}$ and $\boldsymbol{y}$, respectively. Generally speaking, the filtered sample $\hat{\boldsymbol{x}}(\mathbf{t})$ can be expressed as

$$\hat{\boldsymbol{x}}(\mathbf{t}) = \sum_{n=1}^{N-1} c_n(\boldsymbol{y}(\mathbf{t}+\mathbf{p}_n) + \boldsymbol{y}(\mathbf{t}-\mathbf{p}_n)) + c_0 \tag{1}$$

where $\mathbf{t}$ is the location of the to-be-filtered sample, $\mathbf{p}_n$ is the sample location offset to $\mathbf{t}$ according to the filter shape, and $\{c_n | n = 0, 1, \cdots, N-1\}$ are the filter parameters, where c_0 is an offset parameter. Since the symmetric filter shape is adopted, there are only 8, 14, and 22 filter parameters for 5×5, 7×7, and 9×9 filter shapes, respectively.

Based on the mean square error criterion, the optimal filter parameters can be derived by solving the following least square estimation problem, eq. (3) shown at the bottom of this page

$$\min_{\mathbf{C}_k} \sum_{\mathbf{Y}\in\Omega_k} \|\mathbf{Y}\mathbf{C}_k - \mathbf{X}\|_2^2 \tag{2}$$

where Ω_k is the kth set of samples, which share the same filter, and $\mathbf{Y} \in \Omega_k$ represents the vector comprised by the to-be-filtered samples belonging to the set Ω_k. Then, for each class of samples, the corresponding filter parameters are calculated as

$$\mathbf{C} = (\mathbf{Y}^T\mathbf{Y})^{-1}(\mathbf{Y}^T\mathbf{X}). \tag{4}$$

For an image, the pixels usually share different statistical characteristics [23]–[25], which influence the performance of the trained Wiener filers. In the existing works, the gradient-based sample classification method is widely utilized to divide samples into different categories as follows:

$$L(m,n) = \mathrm{dir}(m,n) + Q(A(m,n)) \tag{5}$$

$$\mathrm{dir}(m,n) = \begin{cases} 0, & \text{if } G_h > s_1 \cdot G_v \\ 1, & \text{if } G_v > s_1 \cdot G_h \\ 2, & \text{otherwise} \end{cases} \tag{6}$$

$$A(m,n) = |G_h(m,n)| + |G_v(m,n)| \tag{7}$$

$$Q(A(m,n)) = \begin{cases} 0, & \text{if } A(m,n) > s_2 \\ 1, & \text{otherwise} \end{cases} \tag{8}$$

where $\mathrm{dir}(m,n)$ represents the direction around the sample located at (m,n), $Q(A(m,n))$ represents the sample activities, and s_1, s_2 are constants. The gradients are calculated as

$$\begin{aligned} G_h(m,n) &= 2\boldsymbol{y}(m,n) - \boldsymbol{y}(m,n-1) - \boldsymbol{y}(m,n+1) \\ G_v(m,n) &= 2\boldsymbol{y}(m,n) - \boldsymbol{y}(m-1,n) - \boldsymbol{y}(m+1,n). \end{aligned} \tag{9}$$

In Table I, we show the average PSNR values of all compressed sequences and the corresponding filtered ones with different filter taps. The resolution of the test sequences in Table I is 832×480. The first four frames of these sequences are compressed by HEVC intra coding at $QP = 32$, and then filtered with the derived Wiener filters derived from (2). With the increase of the filter taps, marginal quality improvement of the filtered images is observed, which appears to be less than 0.01 dB. In addition, when more taps are used in the

$$\mathbf{Y} = \begin{pmatrix} 1, \boldsymbol{y}(\mathbf{t}_1+\mathbf{p}_1) + \boldsymbol{y}(\mathbf{t}_1-\mathbf{p}_1), \cdots, \boldsymbol{y}(\mathbf{t}_1+\mathbf{p}_{N-1}) + \boldsymbol{y}(\mathbf{t}_1-\mathbf{p}_{N-1}) \\ \vdots \\ 1, \boldsymbol{y}(\mathbf{t}_M+\mathbf{p}_1) + \boldsymbol{y}(\mathbf{t}_M-\mathbf{p}_1), \cdots, \boldsymbol{y}(\mathbf{t}_M+\mathbf{p}_{N-1}) + \boldsymbol{y}(\mathbf{t}_M-\mathbf{p}_{N-1}) \end{pmatrix}, \mathbf{C} = \begin{pmatrix} c_0 \\ \vdots \\ c_{N-1} \end{pmatrix}, \mathbf{X} = \begin{pmatrix} \boldsymbol{x}(\mathbf{t}_1) \\ \vdots \\ \boldsymbol{x}(\mathbf{t}_M) \end{pmatrix}. \tag{3}$$

TABLE I
PERFORMANCE ON HEVC DECODED IMAGES USING FILTERS WITH DIFFERENT TAPS (IN PSNR)

Images	Decoded Images	5×5	7×7	9×9
BasketballDrill	35.5464	35.5780	35.5936	35.6055
BQMall	35.2243	35.2405	35.2446	35.2526
Keiba	36.4450	36.4635	36.4675	36.4716
PartyScene	32.6086	32.6232	32.6274	32.6351
RaceHorses	34.9494	34.9616	34.9662	34.9686
Average	34.9548	34.9734	34.9799	34.9867

TABLE II
PERFORMANCE ON HEVC DECODED IMAGES USING 5×5 FILTER SHAPE WITH DIFFERENT SAMPLE CLASSIFICATION METHODS (IN PSNR)

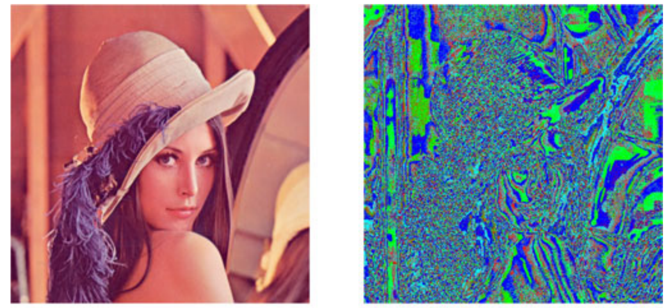
Images	Decoded images	SC1	SC2	SC3
BasketballDrill	35.5464	35.5780	35.5503	37.3327
BQMall	35.2243	35.2405	35.2263	36.3044
Keiba	36.4450	36.4635	36.4571	36.9923
PartyScene	32.6086	32.6232	32.6095	34.0072
RaceHorses	34.9494	34.9616	34.9730	36.7602
Average	34.9548	34.9734	34.9632	36.2794

filter, the overheads for coding filter parameters also increase correspondingly.

Furthermore, we analyze the influences of sample classification on filter performance by using 5×5 filter taps. In particular, three sample classification methods are utilized, including the one described in (5), gradient-based *k*-means clustering methods on the reconstructed and original images, which are denoted as SC1 ($s_1 = 1.5$, $s_2 = 200$), SC2, and SC3, respectively. From the results in Table II, we can see that the quality improvement based on sample classification method SC3 is up to 1.3 dB on average. This is because that the Wiener-based filter targets to minimize the overall distortion, and its performance is limited when samples in an integral set have different statistical characteristics, which cannot be well represented by a single filter. For the worst case, it may not successfully improve the quality of the reconstructed image when there are nearly equal amount of samples with opposite characteristics. Therefore, the sample classification is a vital factor that has largely been ignored in the design of loop-filter in video coding.

B. Near-Optimal Filter Training

Considering the importance of sample classification on the filtering efficiency, we propose a novel scheme to improve the performance of the Wiener-based filters by iteratively learning the near-optimal filter parameters and sample labels simultaneously. In the proposed method, an initial sample classification method is first applied to the reconstructed image, and the optimal filter parameters for samples in each category are derived by solving the optimization problem in (2). Afterward, all the learnt filters are applied to each sample independently, and the optimal filter with minimal distortion between the original and filtered samples is labeled for the corresponding sample. In this manner, each sample is relabeled with a unique filter. The above two procedures, filter derivation and sample relabeling, are performed iteratively until the image quality variation between two successive iterations is smaller than a given threshold.



(a) (b)

Fig. 2. Illustration for the pixel labels on image *Lena*, which is compressed by HEVC intra coding at $QP = 32$. (a) Orignal Lena. (b) Filter Labels.

In the procedure of near-optimal filter learning, the initial sample classification plays an important role in deriving the convergent filters. To analyze the influence of initializations, we utilize 5×5 filter taps in Fig. 1 with different initialization methods to train four filters for each image. We find that the filtering performance fluctuates obviously with different initial labels, and up to 2-dB variations have been observed.

To train the near-optimal filters, we utilize multiple initialization methods to achieve a stable and efficient Wiener filter for each sample category. The best initialization is determined based on the final quality improvement. In this letter, two initialization methods are utilized, i.e., *k*-means method on original and reconstructed images. Herein, the gradient vector in (9) for each pixel is utilized as the feature of *k*-means method, and the features corresponding first K (K is the number of filter labels) pixels in raster scan order as the initial centroids of the *k*-means. The proposed near-optimal filter training algorithm is summarized in **Algorithm 1**.

C. Near-Optimal Filters in Image Compression

Although the proposed near-optimal filters can significantly improve the quality of the compressed images, the side information for sample labels needs to be reproduced at the decoder side, which is difficult to be efficiently predicted. Fig. 2 illustrates an example of the near-optimal sample labels using four filters, where different colors correspond to different labels. Although there are obvious correlations between sample labels and image content, designing an efficient classifier to predict sample labels is still a very difficult problem.

In this letter, considering the correlations among sample labels, we make the first attempt to compress both the near-optimal filter parameters and sample labels into bitstream. In order to improve the compression efficiency, we design two label scan orders to organize them into one-dimensional (1-D) vectors, i.e., run-level coding with horizontal can vertical scan, respectively. Then, the arithmetic coding is applied to these 1-D symbols and the optimal data organization mode with minimal coding bits is selected. For the filter parameters, we directly multiply them by 2^{13} and round them into the nearest integers, which are subsequently encoded with arithmetic coding.

Algorithm 1: Near-Optimal Wiener Filter Training.

Input:
Original and reconstructed images: $\boldsymbol{x}$ and $\boldsymbol{y}$;
The number of filters and initialization methods: K, M;
The threshold for iteration stop: Thr;
Initialization:
Classify the samples into K categories with k-means methods on $\boldsymbol{x}$ and $\boldsymbol{y}$;
while $j \leq M$ **do**
  while $Q_d > Thr$ **do**
    Filter Solving: Solve the filter parameters for samples in each category according to Eqn.(2), $\{\boldsymbol{C}_k | k = 1 \cdots K\}$;
    Sample Re-labelling: Assign each sample with an optimal filter, which achieves the best quality improvement;
    Image Filtering: Filter the image with the optimal sample labels;
    Quality Variations: $Q_d = abs(Q_{cur} - Q_{pre})$; ($Q_{cur}$ and Q_{pre} are the qualities of filtered images in current and previous iterations.)
  end
  Optimal Filter Storage: Save the optimal filter parameters and sample labels into $\boldsymbol{C}_k^{opt}$ and $\boldsymbol{L}$;
  $j = j + 1$;
end
Output: Filter parameters $\{\boldsymbol{C}_k^{opt} | k = 1 \cdots K\}$, and the corresponding optimal sample labels $\boldsymbol{L}$

TABLE III
BITRATE SAVING OF THE PROPOSED METHOD COMPARED WITH HEVC

Images	BDBR (PSNR)	BDBR (SSIM)	Sequences	BDBR (PSNR)	BDBR (SSIM)
Hats	−8.2%	−12.5 %	RaceHorses	−3.8%	−7.0%
Window	−4.1%	−3.1 %	BQSquare	−5.3%	−3.8%
Wharf	−2.8%	−3.9 %	BlowingBubbles	−2.8%	−2.6%
Girl	−3.1%	−3.2 %	BasketballPass	−4.1%	−3.4%
Ahoy	−2.7%	−2.0 %	RaceHorsesC	−4.9%	−4.8%
Statue	−2.6%	−1.9 %	BQMall	−3.6%	−2.3%
Airplane	−4.9%	−4.7 %	PartyScene	−3.8%	−6.6%
Parrot	−4.3%	−1.5 %	BasketballDrill	−3.2%	−1.4%
Average	−4.1%	−4.1 %	Average	−3.9%	−4.0%

III. EXPERIMENTAL RESULTS

To verify the performance of the proposed algorithm, we compare the proposed method with the state-of-the-art image/video coding standard, HEVC. The Kodak test images and HEVC test sequences are used in the comparison experiments. These images are first compressed with HEVC intra coding, then the near-optimal filters and the corresponding sample labels are learnt online and compressed using the proposed method with 50 iterations to learn the near-optimal filters.

For HEVC, HM7.0 software is utilized and all the in-loop filters are turned on, including DF, SAO, and ALF. Two quality metrics, PSNR and SSIM, are utlized in the experiments, especially SSIM [26] metric is more consistent with perceived quality than PSNR. Table III shows the comparison results between the proposed method and HEVC in high bitrate coding scenario. The proposed method achieves about 4.0–4.1% bitrate saving compared with HEVC on average for PSNR and SSIM quality metrics, respectively, and up to 8.2% and 12.5% bitrate saving for image, *Hats*, using PSNR and SSIM metrics, respectively. Since there are many iterations with multiple initial labels, the proposed method also brings extra computational costs. We analyze the computational costs by running the the proposed method and HM7.0 on Windows PC with Intel(R) core(TM) i5-4570 CPU@3.20 GHz. The running time increase of the encoder with the proposed filters is 275% compared with that of the original HM7.0 on average. Fortunately, these operations in the proposed method can be well implemented in parallel, which can be efficiently speeded up for practical applications.

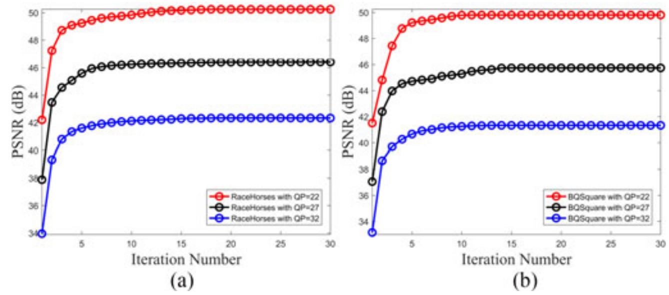


Fig. 3. Quality improvement in each iteration by the proposed near-optimal filters (four filters) for different QPs. (a) RaceHorses. (b) BQSquare.

In Fig. 3, we further show the quality improvement in each iteration during near-optimal filter learning for the compressed images at different *QPs*. The proposed method can consistently improve the reconstructed image quality in terms of PSNR and is convergent due to the greedy algorithm utilized in each iteration. We also try to utilize different number of filters, e.g., two filters for one image. Although the overhead decreases, the filtering performance also degenerates significantly with 3.3% and 0.9% bitrate loss on average using PSNR and SSIM quality metrics, respectively. Therefore, we suggest to utilize four filters for an image in our method. In the future work, we will focus on investigating more sophisticated sample classification methods that are able to predict the optimal results and improve the compression performance, and it is also an interesting problem to adaptively determine the number of the optimal filters for each image, which will be explored in our future work.

IV. CONCLUSION

This letter has proposed a novel near-optimal Wiener filter training method, which iteratively learns the near-optimal filter parameters and sample labels. We have also applied the proposed near-optimal filters to improve the HEVC compression performance by directly compressing both the filter parameters and sample labels. Due to the optimal labels, the proposed method improves the performance of Wiener filters and achieves significant coding gains in high bitrate coding scenario. Moreover, this work points out a new direction for the optimal filtering technique by improving the accuracy of the sample classification.

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