Probabilistic Compression Artifacts Reduction Using Self-Similarity Based Noise Region Estimation

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Abstract— **During compression artifact reduction process, original information as well as noise has been commonly removed, and this side effect should be importantly considered. In this paper, we propose a novel post-processing approach to alleviate the side effect of noise reduction while still reducing compression artifacts successfully. After compression artifact removal using conventional methods, we examine whether the denoised region is actually noisy or not, exploiting the relationship between noisy image and artifact reduced image. Then, the probability of a pixel to be noisy is calculated based on the noise region estimation, and a final denoised pixel is obtained by a weighted average between noisy and denoised signals with the probability. Experimental results show that the proposed method is more effective in preserving texture region while still reducing the compression noise.**

Index Terms— *Compression Artifact Reduction, Self-Similarity, Noise Region Estimation, Probabilistic Noise Removal*

I. Introduction

As user-generated video contents popularly prevail over the Internet, they can be accessed from various multimedia devices such as smart TV and mobile phone. The user-generated video content is typically produced by inexpensive camera and is compressed significantly to reduce storage space, unlike the traditional commercial content production. Thus, it considerably suffers from noise and artifact such as temporal flicker, blocky and mosquito artifacts.

In order to reduce compression artifacts, a couple of methods have been proposed in the literature. Those methods mainly adopt filtering based approach [1]-[6]. Gaussian filter is applied to pixels around block boundaries in order to smooth out blocking artifacts [1]. The authors in [2] proposed non-linear space-variant filters based on edge-oriented classifiers. For the recent decade, non-local means (NLM) denoising algorithms have been studied actively [3]-[5]. They use the similarity between neighboring pixels, and effectively work for the removal of compression artifacts as well as denoising. Takeda et al. [6] proposed a neighboring signal-dependent steering kernel regression to reconstruct a noise image. Even though the filtering based approach is effective for denosing, true edges or texture details are often extremely blurred undesirably in the reconstructed image.

Since compression artifacts are mainly caused by the quantization of transform coefficients, some previous works handle the problem in the DCT domain [7]-[8]. A low-pass filter is applied to the DCT coefficients of block boundary [7]-[8]. Although it has an effect on compression artifacts reduction, image details are still smoothed by the loss of high frequency components.

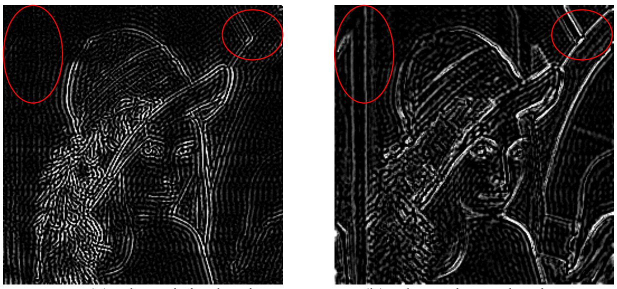
As mentioned above, conventional approaches are effective for the removal of compression artifacts, but blurring is also accompanied essentially. This is a fundamental issue in artifact removal problems, and thus, a trade-off between artifact removal and smoothing should be made optimally.

In this paper, we propose a novel post-processing approach to alleviate the side effect of artifact removal (e.g., blurring) while still reducing compression artifacts successfully. After compression artifact removal using conventional methods, we examine whether the denoised region is actually noisy or not. This is done by exploiting the relationship between noisy image and artifact reduced image for multiple similar patches. Then, the probability of a pixel to be noisy is calculated based on the noise region estimation, and a final denoised pixel is determined by a weighted average between noisy and denoised signals with the noise probability. This basically assumes that there exists a true original pixel between noisy and denoised ones under the assumption of perfect denoising. Experimental results show that the proposed method can reduce blurring, specifically on the texture region while still keeping artifact reduction.

The rest of this paper is organized as follows. In section 2, we describe the image denoising model for our work. The proposed noise region estimation method is presented in section 3. Then, we present the proposed compression artifact reduction method to exploit noise region estimation in section 4. In section 5, performance evaluations are shown. Section 6 finally concludes the paper.

II. Image Denoising Model

Some of the original image data is unavoidably discarded for lossy data compression, and it leads to the occurrence of artifacts. There are several kinds of compression artifacts which are commonly observed in the compressed image. For instance, they are blocking, ringing, and mosquito artifacts which are caused by the mechanisms of image coding such as block-based processing, high frequency loss, and quantization. The goal of compression artifact reduction is to reconstruct the original image (X) from the distorted image (Y).Unlike the additive noises such as Gaussian and salt-and-pepper, some of compression artifacts (e.g., ringing) occur by the loss of high frequency information. Nevertheless, the artifacts are



(a) The original noise (b) The estimated noise

Fig. 1 The illustration of information loss caused by NR process.

visible as if they are additive to the original, and most of artifact reduction methods target at removing them. Thus, the process to remove compression artifacts can be also modeled by a typical denoising process as follows.

$$Y = X + N. \tag{1}$$

where N indicates compression artifacts. Throughout the paper, compression artifact and noise are interchangeably used for the convenience. If an NR (noise reduction) method is applied to the distorted image, noise would be removed to some extent, but unfortunately, noise removal commonly accompanies a side effect of blurring which means the data loss of the original image X, Thus, the denoised image, $\hat{X}$ can be expressed by

$$\hat{X} = Y - L - N. \tag{2}$$

where L is the information loss caused by NR process. If we put (1) into (2), (2) becomes

$$\hat{X} = X - L. \tag{3}$$

The equation, (3) says that NR removes some original data as well as noise additionally. This is typically inevitable for the most of NR methods. Thus, the lost data L should be taken into account importantly during NR process. Our work is motivated by this observation, and deals with how to alleviate the information loss minimally.

An initial experimental result that motivates us is illustrated in Fig. 1. An image is compressed with high ratio, and an NR method is applied to the distorted image. Fig. 1 (a) shows noise which corresponds to the difference between the original and the distorted images, while Fig. 1 (b) represents the difference between the distorted and the denoised images. Fig. 1 (b) consequently includes both the removed noise and the lost data by NR. If both images in Fig. 1 are compared to each other, the information loss is outstandingly visible, particularly to the region marked with red circles.

In this paper, we propose a post-processing NR method. To reduce the loss of original data caused by NR, we first try to identify noisy regions, and if the noisy-free region is actually distorted by NR, it should be recovered as it is. The details are presented in the next section.

III. NOISE REGION ESTIMATION

This section presents how to estimate the noisy region on a pixel basis. The proposed method determines whether a pixel in a compressed image is noisy or not, and exploits the property of self-similarity to identify noisy pixels as shown in Fig. 2 (a). An input noisy image (Y) is partitioned into 5x5 patches, and for each target patch (y_i), *M-1* number of Similar patches (y_i^m) are searched within the noisy image. After searching the similar patches, their counterparts ($\hat{x}_i^m$) are found in the denoised image ($\hat{X}$). We arrange a target patch and all similar patches sequentially together as shown in Fig. 2 (a). Using a pair of a noisy patch and its denoised version, we compute the amount of noise ($n_i(k)$) for the k-th pixel in a patch, y_i as follows.

$$n_i(k) = \sum_{m=1}^{M} s_i^m \cdot \left| y_i^m(k) - \hat{x}_i^m(k) \right|. \tag{4}$$

where $y_i^m(k)$ and $\hat{x}_i^m(k)$ represent the k-th pixel of the patches y_i^m and $\hat{x}_i^m$, respectively. In (4) s_i^m indicates the normalized similarity between a target patch y_i^m and its similar one $\hat{x}_i^m$, and it is given by

$$s_i^m = \frac{w_i^m}{\sum_{m=1}^{M} w_i^m}. \tag{5}$$

where w_i^m represents the similarity between a target patch and its self-similar version, and is measured by

$$w_i^m = \exp\left[-\left(\sum_{k=1}^{25} \left| y_i(k) - y_i^m(k) \right|^2 \right)^{\frac{1}{2}} \right]. \tag{6}$$

It is basically assumed that all noises in the input noisy image have been significantly removed by an NR method. In addition, some original information is inevitably lost with noise together during the NR process. Our ultimate goal is to determine whether each pixel in a noisy image is original information or noisy by examining the amount of the estimated noise.

For quantitative noise measurement of a pixel, we use similar patches as well as a target patch for robust estimation. Under the assumption of perfect artifact removal, the amount of artifacts can be accordingly assumed as the difference between noisy signal and its denoised version. Then, the amount of artifacts is estimated by a weighted sum of all target and similar patches where the weight corresponds to the patch similarity as shown in (4).

Finally, the estimated noise in (4) is thresholded in order to estimate a noisy pixel. If the amount of artifacts exceeds a

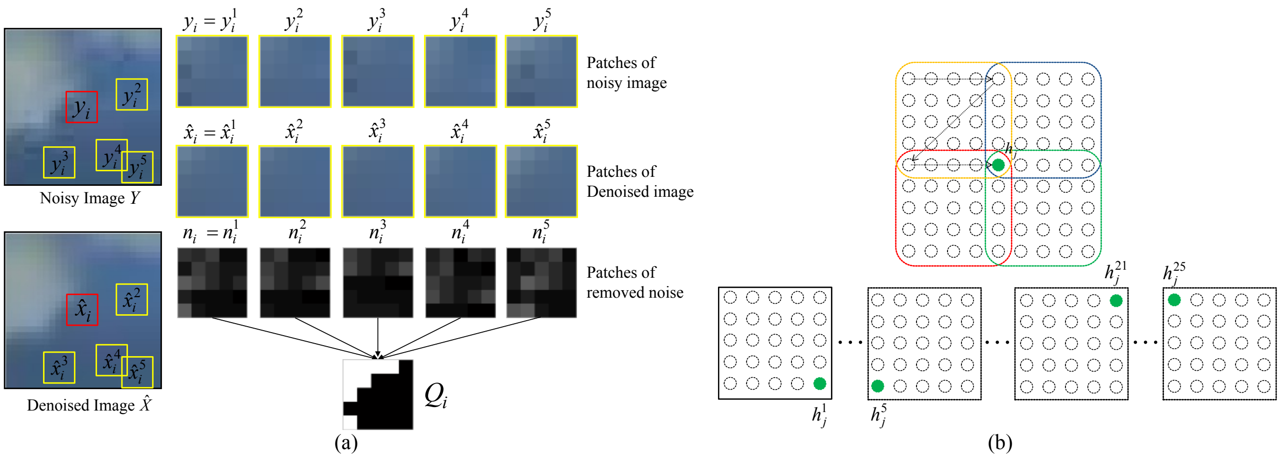


Fig. 2 Self-similarity based noise region estimation;(a) diagram of the noise region estimation and (b) patches including target pixel, h_j for calculating noise probability

pre-defined value (th_n), it is determined that the pixel is originally noisy, and that is given by

$$Q_i(k)=\begin{cases}1, & if\ n_i(k)>th_n \\ 0, & otherwise\end{cases}. \tag{7}$$

where $Q_i(k)$ is a noise indicator for a k-th pixel in a patch, y_i . The large threshold (th_n) makes the output less blurred but less denoised, while the small threshold(th_n) makes the noise removed well but the output smoothed severely. Based on this characteristic, we determine the appropriate threshold empirically. In (7), if the amount of the estimated noise is so small, it is regarded as noise-free. Even though the pixel is noisy really, it is probably difficult to recognize the small noise from a view point of human visual system.

IV. PROBABILISTIC NOISE REMONVAL

In previous section, we present a noise region estimation method where a pixel is determined as either noisy or noise-free. However, it is very challenging to accurately identify a noisy region at a pixel level. Also, as shown in (4), the noise estimation is dependent on the patch similarity. To improve the estimation accuracy, we investigate all patches which include a target pixel. Using these results, this section tries to estimate noisy pixels probabilistically. Then, the probability is used for further denoising by making a trade-off between noisy and complete denoised pixels.

At first, we estimate the noise probability of a target pixel, h_j in an input noisy image. There are 25 patches including a target pixel as shown in Fig. 2 (b). They are denoted by $r(r=1,\ldots,25)$ in a raster scan order and we check whether the target pixel is noisy or not for every patch. Note that depending on the location of the target pixel within a patch, we use different notations. For example, a target pixel is denoted by h_j^r for a patch, r .

For entire 25 patches, we examine whether the target pixel is noise or not using (7) in previous section. Among 25 different estimations, we count the noise estimations only (i.e., $Q_r(h_j^r)=1$), and the noise probability is determined as their relative ratio. Recall that $Q_r(h_j^r)=0$, if h_j is noise-free. Thus, the noise probability of the target pixel, h_j can be given by

$$P(h_j)=\frac{1}{25}\sum_{r=1}^{25}Q_r(h_j^r). \tag{8}$$

Using the probability in (8), NR is additionally performed by a weighted sum of noisy and denoised pixels. Let $\tilde{x}_j$ denote an output pixel produced by the proposed method, and it is computed by

$$\tilde{x}_j=\hat{x}_j\cdot P(y_j)+y_j\cdot(1-P(y_j)). \tag{9}$$

where $\tilde{x}_j$ is the denoised pixel by an NR method and y_j is an input noisy pixel. We repeat the process of (9) for all pixels in an input image, and the further denoised image is obtained.

V. EXPERIMENTAL RESULT

The noise input image is obtained by applying *JPEG* lossy compression to the original clean image from Berkeley dataset. In all experiments, we set the compression quality factor to 50 and the patch size to 5x5 and use the luminance intensity of the noisy image for denoising. The noisy image is initially denoised by the existing NLM [4] and SKR [6], and then, the proposed post-processing is applied for further optimal denoising. We compare the capabilities between the proposed and existing NR methods in terms of both compression artifact removal and the preservation of the original texture information.

Fig. 3 shows the result of the test image, *fire man*. The noisy image in Fig. 3 (a) exhibits compression artifacts such as blocking and ringing on the whole. As shown yellow

(a) (b) (c)

Fig. 3 Subjective quality comparisons
(a) the noisy image (QF=50), (b) NLM [4], (c) ours with NLM [4]

(a) (b) (c)

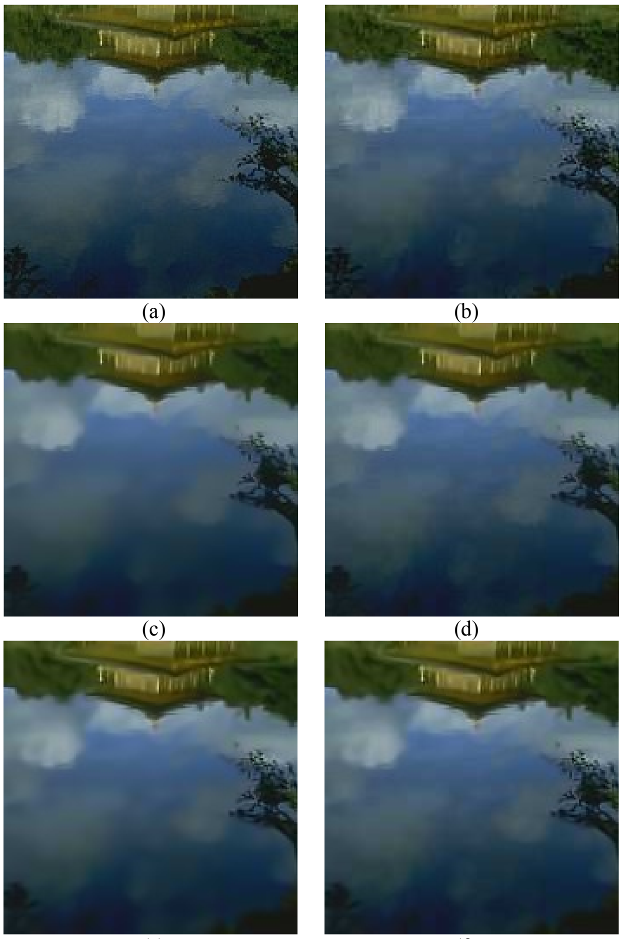
Fig. 4 Estimated noise comparisons
(a) original clean image, (b) removed noise using NLM [4], (c) removed noise using ours

ellipse in Fig. 3 (b), NLM suffers from severe blurring on the texture region such as sleeve of fire man while it removes compression artifacts effectively. On the contrary, the proposed method in Fig. 3 (c) preserves more details in the texture region while still reducing compression artifacts.

Fig. 4 (b) and (c) represent the quantity of the data removed by NLM and the proposed method, respectively in the red box of Fig. 4 (a). As shown in Fig. 4 (c), the proposed method removes less data in the texture regions such as water and cloud than NLM. Actually, the data removed by NLM in those regions correspond to the original information, not artifact. In other words, texture information is preserved better in the proposed method. For the red box of Fig. 4 (a), Fig. 5 compares the visual quality subjectively. All methods surely remove compression artifacts (e.g., around the leaves of right side and within the cloud of left side) well. However, the clouds reflected in water are blurred severely in the existing methods as shown in Fig. 5 (c) and (e). Meanwhile, the proposed method recovers the details in the region, which have been already removed by NR initially.

VI. CONCLUSION

This paper presents a novel post-processing approach to alleviate the side effect of conventional NR methods (e.g., blurring) while still reducing compression artifacts successfully. Through a pair of similar patches searched from noisy and denoised images, we estimate whether the denoised region is actually noisy or not at a pixel level. Then, the probability of a pixel to be noisy is calculated by repeating noise estimation for all possible patches to include the pixel. A final denoised pixel is obtained by a weighted average between noisy and denoised signals with the probability. Experimental results show that the proposed method is more effective in preserving texture region while still reducing the compression noise. In addition, the proposed method can work with any NR method harmoniously.



(a) (b) (c) (d) (e) (f)

Fig. 5 Subjective quality comparisons
(a)-(f) enlargement of red box in Fig. 4 (a),
(a) original clean image, (b) the noisy image (QF=50), (c)NLM [4], (d) ours with NLM [4], (e) SKR [6], (f) ours with SKR [6]

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