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Correlation based universal image/video coding loss recovery

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ABSTRACT

Coding artifacts are annoying in highly compressed signals. Most of the existing artifact reduction methods are designed for one specific type of artifacts, codecs, and bitrates, which are complex and exclusive for one type of artifact reduction. Since both the compressed image/video and the coding error contain information of the original signal, they are highly correlated. Therefore, we try to recover some lost data based on the correlation between the compressed signal and the coding error, and introduce a novel and universal artifact reduction method. Firstly, according to the spatial correlation among pixels, a pixel-adaptive anisotropic filter is designed to reconstruct the distorted signal. Next, a globally optimal filter is designed to further recover the coding loss. Experimental results demonstrate that within an extensive range of bitrates, the proposed method achieves about 0.8 dB, 0.45 dB, 0.3 dB, and 0.2 dB on average of PSNR improvement for JPEG, MPEG4, H.264/AVC, and HEVC compressed signals, respectively.

1. Introduction

Due to the limited available bandwidth and storage, image/video signals need to be compressed with reduced bitrates [1]. During the lossy image/video compression (e.g., JPEG, JPEG2000, MPEGx, H.26x, etc.), the quantization process causes artificial discontinuity, such as blocking, ringing, mosquito noise, and so on [2,3]. In order to ameliorate the qualities of compressed images/videos, appropriate postprocessing techniques are required at the decoder side [4,5].

In the past decade, a series of coding artifact reduction methods have been introduced. In the early stage, according to the dominant blocking artifacts in low bit rate, many deblocking methods, which result in filtration (e.g., low-pass or average property) of signals [6–10], were proposed. In fact, these deblocking procedures are smoothing operators, which smooth out both the blocking artifacts and image details (e.g., texture and edge). In order to minimize the damage to the image details (e.g., texture and edge) and remove the blocking artifacts, many post-filtering schemes assume that most artifacts occur at some predictable positions [11–15]. However, for MPEGx or H.26x compression, the blocking artifacts may occur anywhere of a frame as a result of motion compensation [16–18]. Therefore, the positions where the blocking artifacts appear are unable to be predicted [13,19] for MPEGx or H.26x compression. In addition, image regions with different types of contents (i.e., plain, texture, edge, etc.) are firstly discriminated for adaptive processing [20–22]. However, the discrimination of image contents is extremely difficult, and it is also hard to accurately separate the blocking/ringing artifacts from the edge/texture information. Besides, these existing approaches are content and codec dependent, and too many models and parameters need to be decided. As a result, these existing approaches are restricted to certain types of codecs, artifacts, and bitrates. Therefore, a universal coding artifact reduction method is required.

In essence, the coding artifact reduction procedure can be viewed as an attempt of coding loss recovery (the error between the original and the compressed images) [19]. Therefore, we try to reduce the coding artifacts by reconstructing/recovering image content in the decoder side according to the correlations of image pixels. It is well known that image contents are highly correlated with their surroundings [23], and these correlated contents jointly present some self-similar structures [24]. The structural self-similarity is widely explored for image recovery. For example, according to the characteristics of structures, distortions can be accurately removed for image denoising [25,26]; distorted structures can be efficiently recovered for image deblurring [27] and reconstruction [28,29]. Moreover, in image compression, the compressed and lost parts usually present some common structural information of the original image. In other words, the coding loss is also correlated with the compressed image [19,30]. Therefore,

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we can recover the coding loss according to its correlation with the compressed image.

In this paper, we try to recover the coding loss according to the correlation properties among image/video contents, and introduce a universal artifact reduction algorithm. Firstly, we analyze the relationship between the compressed image/video and the coding error. Secondly, the structural characteristics of the compressed image is explored, and a pixel-adaptive anisotropic filter is designed to reconstruct the distorted contents by exploiting these highly correlated pixels. Thirdly, based on the correlation between the compressed image and the coding error, a global optimal filter is designed to further recover the coding loss. Since the proposed algorithm recovers the lost data based on the correlation among image/video contents, it is not restricted to one specific artifact type. The proposed algorithm is applicable to all codecs under any bitrate. Experimental results on JPEG, MPEG4, H.264/AVC, and HEVC codecs demonstrate the effectiveness of the proposed algorithm.

The rest of this paper is organized as follows. In Section 2, we explore and illustrate the correlation between the compressed image and the coding loss. The detailed recovery implementation of the proposed artifact reduction method is presented in Section 3. Then, in Section 4 the performance of the proposed method is demonstrated. Finally, we draw the conclusions in Section 5.

2. Image correlation analysis

During the lossy compression, some visual information is discarded through the coefficient quantization, which reduces the amount of data for transmission and storage [16,17]. Let $I(x)$ denotes a pixel in the original image, and $I_c(x)$ denotes the pixel in the compressed image (e.g., with JPEG, JP2K, MPEG4, etc.). The compression loss (discarded information, ΔI) can be expressed as,

$$\Delta I(x) = I(x) - I_c(x), \tag{1}$$

where $\Delta I(x)$ is the lost data of pixel $I(x)$.

Generally, the compressed image I_c possesses the main contents of the original image, and the compressed loss ΔI contains the residual information of the original image. Both of them possess the structural information of the original image, and jointly present the visual contents. An example of JPEG coding is shown in Fig. 1, in which (b) and (c) are the compressed and lost parts of (a). As can be seen, though Fig. 1b is distorted by noticeable artifacts, we can acquire most of the visual information from Fig. 1b as that provided by the original image (Fig. 1a); meanwhile, Fig. 1c presents the coarse contours of objects in Fig. 1a, with which we can imagine and recognize objects in the original image (i.e., peppers in Fig. 1a). In summary, Fig. 1b and c present some common structural information of Fig. 1a (though Fig. 1b provides more detailed structures and Fig. 1c only shows the coarse structures of the original image). Therefore, the contents of the compressed image and the lost data are correlated at certain level.

In order to further illustrate the correlation between the compressed image and the lost data, a thorough analysis on image content similarity is made. Structural information represents the main content of an image, which is adapted to be extracted for image perception and understanding [31,32]. Therefore, we try to extract structural information from images for content similarity analysis. From the view of image processing, global image structure is usually represented by local binary pattern based histogram [33], and local image structure is always represented by luminance difference [34] or local variance [31]. In this work, the local variance on luminance is adopted for local structure analysis,

$$\mathcal{V}(x) = \frac{1}{(2r+1)^2}\sum_{\Delta x}\left(I(x+\Delta x) - \bar{I}(x)\right)^2, \tag{2}$$

$$\bar{I}(x) = \frac{1}{(2r+1)^2}\sum_{\Delta x} I(x+\Delta x), \tag{3}$$

where $\mathcal{V}(x)$ is the variance of pixel $I(x)$, Δx is the location shift in the local region, $\bar{I}(x)$ is the local mean value of pixel $I(x)$, and r is the radius of the local region.

According to the Pearson correlation function [35], the structural correlation between the compressed image and the lost data can be computed as,

$$\mathcal{C}(I_c, \Delta I) = \frac{1}{N}\sum_x \frac{\sum_x(\mathcal{V}_c(x) - \overline{\mathcal{V}}_c)(\mathcal{V}_d(x) - \overline{\mathcal{V}}_d)}{\sqrt{(\sum_x(\mathcal{V}_c(x) - \overline{\mathcal{V}}_c)^2)(\sum_x(\mathcal{V}_d(x) - \overline{\mathcal{V}}_d)^2)}}, \tag{4}$$

where $\mathcal{C}(I_c, \Delta I)$ is the similarity coefficient between I_c and ΔI; N is the total pixel number of image I_c; $\mathcal{V}_c$ is the structural information of the compressed image I_c, and $\overline{\mathcal{V}}_c$ is the average value of $\mathcal{V}_c$; $\mathcal{V}_d$ is the structural information of the lost data ΔI, and $\overline{\mathcal{V}}_d$ is the average value of $\mathcal{V}_d$.

Four oft-used images (i.e., Pepper, Boat, Barbara, and Huts) are chosen for correlation analysis, which are mainly composed by smooth, edge, regular texture, and irregular texture, respectively. The four images are compressed with JPEG codec under five different bitrates (i.e., 0.25, 0.5, 1, 2, and 3 bpps), and the correlations between these compressed images and their corresponding lost data are computed with (4). The correlation coefficients of these images are listed in Table 1, and their corresponding statistical values are shown in Fig. 2. From Table 1 and Fig. 2 we can see that under high bitrate (e.g., 3 bpp), the compressed images are less correlated with their corresponding lost data; whereas under low bitrate (e.g., 0.25 bpp), the correlations between the compressed images and their lost data are strong. This is because under high

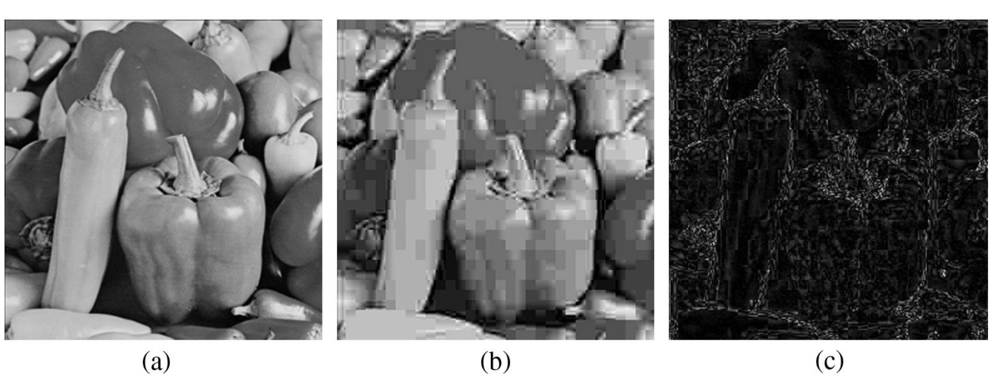

Fig. 1. An example of correlation between the coded image and the lost data. (a) The original image. (b) JPEG coded image. (c) Lost data, in which the values are mapped into [0, 255] for a better view.