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Image postprocessing by Non-local Kuan's filter

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A B S T R A C T

Blocking artifacts exist in images and video sequences compressed to low bit rates using block-based discrete cosine transform (DCT) compression standards. In order to reduce blocking artifacts, two image postprocessing techniques, DNLK filter and OCDNLK filter, are presented in this paper. A more accurate DCT domain Kuan's filter based on Non-local parameter estimation was proposed from the linear minimum mean-square-error (MMSE) criterion. We analyze the required two assumptions for the filter theoretically. Then the DCT domain Kuan's filter for low frequency coefficients and Non-local mean filter for high frequency AC coefficients constitute the proposed Non-local Kuan's (NLK) filter. After that, we propose the Dual Non-local Kuan's (DNLK) filter by applying the proposed filter in dual layer. The DNLK filter is extended to form the Overcomplete Dual Non-local Kuan's (OCDNLK) filter by applying to the overcomplete DCT coefficients. Experimental results on coded images using test quantization tables and JPEG coded images show the effectiveness of the two methods.

1. Introduction

Block-based discrete cosine transform (DCT) coding is adopted in several industry standards, such as JPEG, MPEG, and H.264, for image and video compression. In a block-based DCT scheme, an image is firstly divided into non-overlapping blocks and pixels in each block are transformed into the DCT coefficients which are then quantized. At low bit rates, blocking artifacts will be visible, because quantization is performed independently at each block without considering the existing correlations among adjacent blocks. The use of a postprocessing technique on a coded image is a common strategy to reduce blocking artifacts and improve fidelity, as it does not require modifications of existing image/video standards and so is readily available. Based on different types of postprocessing techniques, such as post-filtering, iterated projection onto convex sets (POCS), maximum a posteriori (MAP) estimation, overcomplete wavelet, a variety of postprocessing methods have been developed to cope with the problem.

Early attempts used image enhancement approach. For example, Lim and Reeve [1] applied low-pass filtering to pixels along block boundaries. This method sometimes blurs true edges, so some adaptive post-filtering techniques were proposed. Ramamurthi and Gersho [2] applied 2D low-pass filtering only to areas away from edges and performed 1D filtering to areas near edges to avoid blurring them. The post-filtering techniques used in recent coding standards such as H.264/AVC [3] and MPEG-4 [4] consist of several filters and one of them is selected based on local activity. The abovementioned methods are performed in the spatial domain. Recently, some post-filtering techniques in the DCT domain were proposed [5–7], which have demonstrated that postprocessing in transform domain is a promising postprocessing approach.

Methods based on POCS techniques [8–12] were also proposed. The idea is to impose smoothness constraint around block boundaries and project block images onto these convex sets (POCS) iteratively. Both forward and inverse DCT are required in each iteration, so the major drawback is high computational complexity. In order to reduce computation, Gan et al. [12] proposed a novel smoothness constraint set in the DCT domain and used the iterative POCS technique to reduce blocking artifacts.

By formulating postprocessing as an inverse problem, the MAP estimation technique can be used to find the solution. The probability function of the original image is modeled by different Markov random field (MRF) models [13–17]. Sun and Cham [16,17] modeled the original image as a high order MRF using the Fields of Experts (FoE) framework, and proposed an effective postprocessing method by MAP criterion. Li and Delp [18] addressed the problem using a DCT domain MRF model to do the MAP estimation.

As to the overcomplete wavelet technique [19–21], it uses the overcomplete wavelet representation to reduce blocking artifacts. Xiong et al. [19] used thresholding of the overcomplete wavelet coefficients to reduce the quantization effects. In [20] the wavelet transform modulus maxima representation was adopted for deblocking. Liew and Yan [21] analyzed the block discontinuities caused by coding to derive more accurate thresholds at different

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wavelet scales. Recently, a novel deblocking method based on the shape-adaptive DCT [22] was developed, which achieved the best performance until now.

Kuan's filter [24] can produce the linear minimum mean-square-error (MMSE) for a signal corrupted with uncorrelated, signal-dependent noise. We develop a more accurate DCT domain Kuan's filter using Non-local parameter estimation technique. Two assumptions are needed to derive the solution of the filter. We investigate the validity of the assumptions and verify each of them. The DCT domain Kuan's filter is applied for low frequency DCT coefficients that satisfy the two assumptions and Non-local mean filter is used for high frequency AC coefficients. Then we have the proposed Non-local Kuan's (NLK) filter. A new image post-processing method called Dual Non-local Kuan's (DNLK) filter is then proposed. It uses the NLK filter to obtain good estimates of image statistics and then applies the NLK filter again to reduce quantization noise. We also found that the proposed NLK filter can be used for the estimation of the overcomplete DCT coefficients. Hence, the DNLK filter is combined with the overcomplete representation to form the Overcomplete Dual Non-local Kuan's (OCDNLK) filter. Experimental results show that the OCDNLK filter, in most cases, can achieve higher PSNR gain than other state-of-the-arts methods and generates images with the best visual quality. The performance of the DNLK filter, which has lower complexity than the OCDNLK filter, is comparable to other state-of-the-arts methods. Moreover, we demonstrate the efficiency of the two methods on JPEG coded images under various image quality settings.

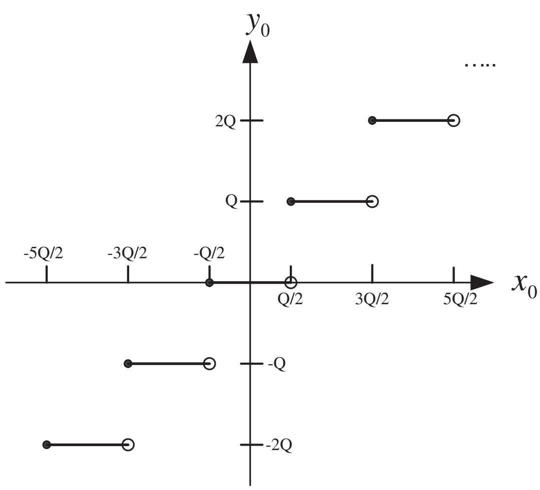

Fig. 1. A staircase-type roundoff quantizer.

In Section 2, we explain the proposed Kuan's filter in the DCT domain using Non-local parameter estimation technique which achieves LMMSE, analyze the two assumptions required, and finally develop the NLK filter used for all DCT coefficients. Section 3 presents the two image postprocessing methods, DNLK filter and OCDNLK filter. Experimental results on images using test quantization tables and JPEG coded images are given in Section 4. Finally we draw conclusions in Section 5.

2. The proposed Non-local Kuan's filter in the DCT domain

A roundoff quantizer is a non-linear device having a staircase-type input–output characteristic as shown in Fig. 1. At the transmitting end, if we know the original DCT coefficients x_0 and quantization step Q, the quantized value $y_0 \in \{rQ\ ;\ r = 0, \pm1, \pm2, \ldots\}$ and quantization error n will be determined. However, at the receiving end, we have the quantized value y_0, and only know that error n is in the range $[-Q/2, Q/2]$ and the input x_0 is in the range $[y_0 - Q/2, y_0 + Q/2]$. Let $y_0 = x_0 + n$, where n is the additive zero-mean noise introduced by the quantizers and contributes to the blocking artifacts in the coded image. The problem here is to estimate x_0 from y_0 and the quantizer information.

2.1. LMMSE filter in the DCT domain

Let $B_{m,n}$ be an 8×8 block at the mth block row and nth block column in an image, and $B_{m,n}^{k,l}$ be the block with k shifts in the horizontal direction and l shifts in the vertical direction, relative to the block $B_{m,n}$. Fig. 2(a) gives two examples with $k = -1$, $l = -1$ and $k = 1$, $l = 0$, respectively. When $|k| \leqslant 1$ and $|l| \leqslant 1$, there are 8 shifted blocks $B_{m,n}^{k,l}$ neighboring the block $B_{m,n}$. We apply the DCT on each of the shifted blocks. Hence, for each coefficient y_0 in $B_{m,n}$, there are 8 neighboring coefficients y_i, $i = 1, 2, \ldots, 8$ from the 8 shifted blocks $B_{m,n}^{k,l}$, $|k| \leqslant 1$, $|l| \leqslant 1$ as shown in Fig. 2(b).

Consider the noise model $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{n}$, where vector $\boldsymbol{n}$ represents the noises, vector $\boldsymbol{y}$ contains the quantized coefficient y_0 and its neighboring coefficients y_i, $i = 1, 2, \ldots, K$ from shifted blocks, and vector $\boldsymbol{x}$ contains the corresponding original coefficients x_0 and x_i, $i = 1, 2, \ldots, K$. Let the filter coefficients be $\boldsymbol{h}$, then the estimated original DCT coefficients $\hat{\boldsymbol{x}} = \boldsymbol{hy}$. According to the linear minimum mean square error (LMMSE) estimator [23], we have

$$\hat{\boldsymbol{x}}_{\boldsymbol{LMMSE}} = (\hat{x}_0, \hat{x}_1, \ldots, \hat{x}_K)^T = E[\boldsymbol{x}] + C_{xy}C_y^{-1}(\boldsymbol{y} - E[\boldsymbol{x}]), \tag{1}$$

where $E[\boldsymbol{x}]$ is the ensemble mean of $\boldsymbol{x}$, $C_{\boldsymbol{xy}}$ is the cross-covariance matrix of $\boldsymbol{x}$ and $\boldsymbol{y}$, and $C_{\boldsymbol{y}}$ is the covariance matrix of $\boldsymbol{y}$.

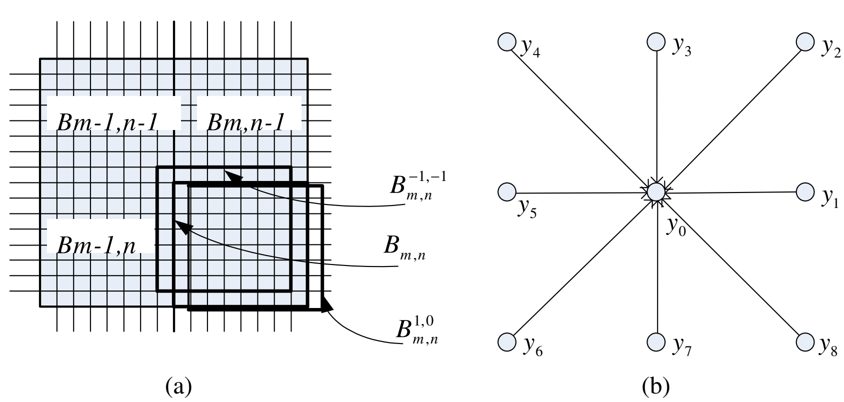

Fig. 2. (a) Shifted block representation (b) 3×3 context window.