Quality Enhancement of DDBTC Decoded Image

Joni Welman Simatupang
Study Program of Electrical Engineering
President University
Bekasi, Indonesia
joniwsmtp@president.ac.id

Heri Prasetyo
Department of Informatics
Universitas Sebelas Maret
Surakarta, Indonesia
heri.prasetyo@staff.uns.ac.id

***Abstract*— This paper presents two methods for improving the quality of Dot Diffused Block Truncation Coding (DDBTC) decoded image. The first method exploits the usability and effectiveness of decimated Discrete Wavelet Transform and stationary Wavelet Transform for reducing the half-toning artifact. While, the second method employs the Vector Quantization (VQ) approach for performing the image patch replacement and suppressing the unpleasant artifact of DDBTC decoded image. As documented in Experimental Section, these two methods performs well for improving the quality of DDBTC decoded image.**

Keywords*— *dot diffused, image enhancement, vector quantization, wavelet

I. Wavelet-Based Quality Improvement

Let I be an input image of size $M \times N$. Typically, the input image is in grayscale. However, the DDBTC method can be easily extended to the color image. DDBTC scheme firstly divides I into several non-overlaping blocks of size $m \times m$. Suppose that i is the processed image block. The DDBTC converts and encodes i into another form as follow [1]:

$$i \Rightarrow \{t_{min}, t_{max}, b\}, \tag{1}$$

where t_{min} and t_{max} denote the minimum and maximum quantizer, respectively. b is the bitmap image of size $m \times m$. In 8-bits pixel representation, DDBTC reduces the required bits for storing a single image block from $8m^2$ bits to be $2 * 8 + m^2$ bits. The DDBTC employs the class matrix and error diffused kernel for generating b [1-3].

In the decoding process, the DDBTC reconstructs t_{min}, t_{max}, and b into the original image block. This process is denoted as:

$$\hat{\imath} \Leftarrow \{t_{min}, t_{max}, b\}, \tag{2}$$

where $\hat{\imath}$ denotes the reconstructed image block of size $m \times m$. Each pixel in $\hat{\imath}$ is composed from t_{min} or t_{max} based on the value of b. This substitution process is given as follow:

$$\hat{\imath}(x,y) = \begin{cases} t_{min}, & \text{if } b(x,y) = 0 \\ t_{max}, & \text{if } b(x,y) = 1 \end{cases}, \tag{3}$$

for $x, y = 1,2, \dots, m$. One obtains the DDBTC decoded image $\hat{I}$ by collecting all image blocks $\hat{\imath}$.

The wavelet-based image enhancement aims to improve the quality of DDBTC decoded image by exploiting the decimated and stationary wavelet transform. Specifically, this process is denoted as follow:

$$\tilde{I} \Leftarrow \psi\{\hat{I}\}, \tag{4}$$

where $\tilde{I}$ and $\psi\{\cdot\}$ are the enhanced DDBTC decoded image and operator of wavelet-based image enhancement, respectively. The quality of enhanced image should be as similar as possible to that of the original image, i.e. $\tilde{I} \approx I$.

In the wavelet-based enhancement, the DDBTC decoded image $\hat{I}$ is firstly downsampled by factor 0.5 with bicubic interpolator. It indicates that the image size of $\hat{I}$ reduces from $M \times N$ into $\frac{M}{2} \times \frac{N}{2}$. Subsequently, we perform the wavelet transforms on $\hat{I}$ as:

$$\mathcal{W}\{\hat{I}\} \Rightarrow \{\hat{I}_{\phi} | \phi = (LL, LH, HL, HH)\}, \tag{5}$$

$$\mathcal{S}\{\hat{I}\} \Rightarrow \{\hat{I}_{\phi_s} | \phi_s = (LL, LH, HL, HH)\}, \tag{6}$$

where $\mathcal{W}\{\cdot\}$ and $\mathcal{S}\{\cdot\}$ denote the operator of decimated wavelet and stationary wavelet transform, respectively. In this paper, we utilize the Daubechies 1 (db1) for $\mathcal{W}\{\cdot\}$ and $\mathcal{S}\{\cdot\}$. The symbols $\hat{I}_{\phi}$ and $\hat{I}_{\phi_s}$ are the transformed DWT and SWT sub-bands, respectively. Both are of sizes $\frac{M}{4} \times \frac{N}{4}$ and $\frac{M}{2} \times \frac{N}{2}$, respectively. Each image sub-band $\hat{I}_{\phi}$ is further upsampling with factor 2 using bicubic interpolator to obtain the image sub-band of size $\frac{M}{2} \times \frac{N}{2}$.

Simple additive operation is then applied for each image sub-band $\hat{I}_{\phi}$ and $\hat{I}_{\phi_s}$ as bellow:

$$A_{\phi} \Leftarrow \lambda_{\phi} \hat{I}_{\phi} + (1 - \lambda_{\phi}) \hat{I}_{\phi_s}, \tag{7}$$

where A_{ϕ} is fusion between $\hat{I}_{\phi}$ and $\hat{I}_{\phi_s}$, for all $\phi = (LL, LH, HL, HH)$. The symbol λ_{ϕ} is the additive scaling factor controlling the strength of $\hat{I}_{\phi}$ and $\hat{I}_{\phi_s}$. The size of A_{ϕ} is $\frac{M}{2} \times \frac{N}{2}$. At the end, an inverse DWT operation is executed as follow:

$$\tilde{I} \Leftarrow \mathcal{W}^{-1}\{A_{\phi} | \phi = (LL, LH, HL, HH)\}, \tag{8}$$

where $\mathcal{W}^{-1}\{\cdot\}$ denotes the inverse DWT operator, and $\tilde{I}$ is the DDBTC reconstructed image of size $M \times N$. The wavelet-based approach effectively suppresses the occurred impulsive noise on DDBTC decoded image.

II. VQ-Based Quality Improvement

This section presents the quality enhancement of DDBTC decoded image using VQ approach. This method requires a set of training images denoted as $T = \{t_k | k = 1,2, \dots, N_T\}$, where N_T is the number of training images, i.e. original image without compression. Let $C = \{C_1, C_2, \dots, C_{N_c}\}$ be a codebook of size N_c obtained from VQ training over T. The symbol C_k denotes the k-th codeword of size $n \times n$, for $k = 1,2, \dots, N_c$. We firstly extract image patch p of $n \times n$ from the DDBTC decoded image $\hat{I}$. Herein, we use overlapping strategy on image patch extraction process. Subsequently, we perform similarity matching between p with C_k with Euclidean distance as follow:

$$k^* \Leftarrow \arg \min_{k=1,2,\dots,N_c} \|p - C_k\|_2^2, \tag{9}$$

where k^* is the index of the most similar codeword C_k in C. Then, the image patch p is simply replaced with codeword C_{k^*}, i.e. the most closest codeword, as follow:

$$\tilde{p} \Leftarrow C_{k^*}, \tag{10}$$

where $\tilde{p}$ is the replaced image patch.

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The procedure of image patch replacement is performed over all overlapping image patches. By collecting all image patches $\tilde{p}$, we obtain an non-alignment DDBTC reconstructed image as follow:

$$\tilde{o}(x,y) \Leftarrow \cup_{\forall \tilde{p}} \tilde{p}. \quad (11)$$

An alignment process is then executed to obtain a correct DDBTC enhanced image. This process is defined as bellow:

$$\tilde{I}(x,y) \Leftarrow \frac{\sum \tilde{o}(x,y)}{\sum R^T(x,y)R(x,y)}, \quad (12)$$

where $R(x,y)$ is the image patch operator. At the end of VQ-based processing, we obtain the enhanced DDBTC decoded image $\tilde{I}$ of size $M \times N$.

III. Experimental Results

We investigate the performances over four color images as displayed in Fig. 1, each of size 512×512. Herein, the wavelet and VQ-based methods perform image enhancement over all color spaces, i.e. Red, Green, and Blue individually. The wavelet-based approach utilizes λ_ϕ as $\{0.8, 0.7, 0.7, 0.6\}$ for wavelet sub-bands $\{LL, LH, HL, HH\}$. Whereas, the VQ codebook is generated from standard images (Lena, Baboon, Lake, and Peppers) as training set.

A. Visual Investigation

The visual investigation between the wavelet and VQ-based methods is reported in this sub-section. We use the codebook of size $N_c = 256$ for VQ-based approach. The DDBTC image block size is set as $m \times m = 8 \times 8$. Fig. 2 demonstrates the enhancement results of DDBTC decoded image. The first row is the DDBTC decoded image. Whereas the second and third rows are the enhanced images from wavelet and VQ-based method, respectively. As shown in Fig. 2, these two aforementioned schemes improve the quality of DDBTC decoded image. The result from VQ-based scheme is visually better compared to that of the wavelet-based approach.

B. Objective Evaluation

This sub-section summarizes the performance of wavelet and VQ-based approaches in terms of objective image quality assessments. We consider two objective metrics, i.e. Peak-Signal-to-Noise-Ratio (PSNR) and Structural Similarity Index Metric (SSIM), to examine the performance. All images in Fig. 1 are turned as testing image. The average PSNR and SSIM scores are subsequently computed over all testing images. In this experiment, we employ several codebooks over different sizes, i.e. $N_c = 16, 32, \ldots, 256$. Table I tabulates the performance comparisons between the wavelet and VQ-based approaches on quality enhancement of DDBTC decoded images. These two aforementioned methods effectively improves the image quality as indicated with increasing average PSNR and SSIM values in comparison with the DDBTC decoded image. The VQ-based approach offers better performance compared to that of the wavelet-based method. Yet, the proposed quality enhancement methods yield acceptable results based on visual investigation as well as objective measurement.

References

[1] Y. F. Liu and J. M. Guo, "Dot-diffused halftoning with improved homogeneity," *IEEE Trans. Image Process.*, vol. 24, no. 11, pp. 4581-4591, Nov. 2015.

[2] J. M. Guo, H. Prasetyo and N. J. Wang "Effective image retrieval system using dot-diffused block truncation coding features," *IEEE Trans. Multimedia*, vol. 17, no. 9, pp. 1576-1590, Sep. 2015.

[3] H. Prasetyo and H. Kurniawan, "Reducing JPEG False Contour Using Visual Illumination," *Informations*, vol. 9, no. 2, pp. 41, 2018.

Fig. 1. A set of testing images in color space.

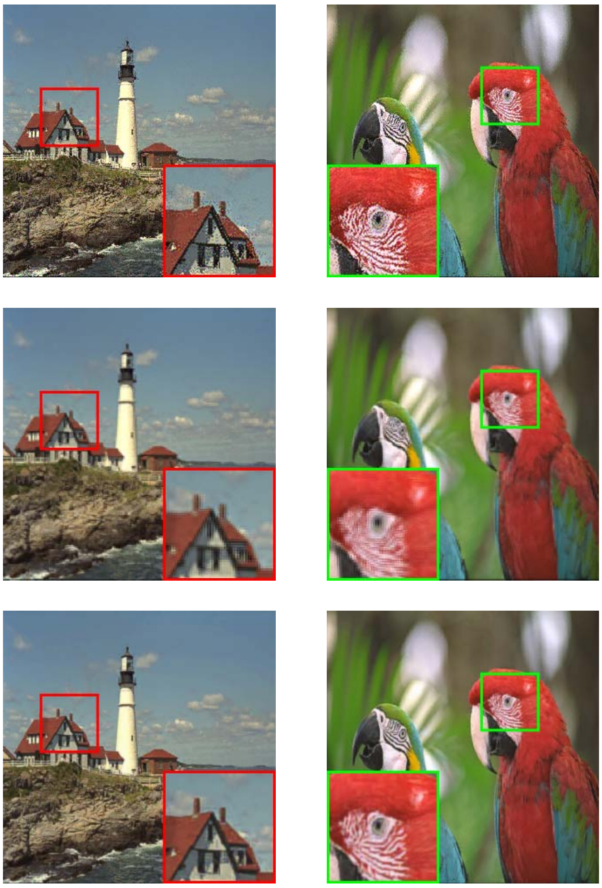

Fig. 2. The quality enhancement of DDBTC decoded images: (first row) DDBTC decoded image, (second row) enhanced image with wavelet-based approach, and (third row) enhanced image from VQ-based method.

TABLE I. Evaluations in Terms of Average PSNR and SSIM Scores

Method	Average PSNR	Average SSIM
DDBTC Decoded Image	20.52	0.74
Wavelet-Based Method	24.97	0.84
VQ-Based Method, $N_c = 16$	26.05	0.86
VQ-Based Method, $N_c = 32$	27.80	0.91
VQ-Based Methd, $N_c = 64$	28.44	0.92
VQ-Based Method, $N_c = 128$	28.89	0.93
VQ-Based Method, $N_c = 256$	29.25	0.94