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Deblocking Joint Photographic Experts Group Compressed Images via Self-learning Sparse Representation

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ABSTRACT

Joint Photographic Experts Group (JPEG) is one of the most widely used image compression methods, but it causes annoying blocking artifacts at low bit-rates. Sparse representation is an efficient technique which can solve many inverse problems in image processing applications such as denoising and deblocking. In this paper, a post-processing method is proposed for reducing JPEG blocking effects via sparse representation. In this method, a dictionary is learned via the single input blocky image using K-SVD. There is no need for any prior knowledge about the blocking artifacts. Experimental results on various images demonstrate that the proposed post-processing method can efficiently alleviate the blocking effects at low bit-rates and outperform some new well-known image deblocking methods.

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1. INTRODUCTION

JPEG is the most popular compression technique due to its low computational complexity and simplicity in hardware implementation. In JPEG encoding, an image is divided into 8×8 non-overlapping blocks, then the discrete cosine transform (DCT) is applied on each block. Afterward, the quantization operation is applied on the DCT coefficients. The quantization of the DCT coefficients may cause blocking effects in the compressed image. The unpleasant blocking effect is due to the omission of correlation among spatially adjacent blocks in the transformation and quantization, i.e., each block is separately transformed using DCT and is quantized without considering the neighbouring pixels in adjacent blocks [1, 2]. The unpleasant blocking effects are more serious on the decoded image at low bit-rates, because of the coarse quantization. It is noteworthy that in internet and mobile multimedia applications, images usually need to be compressed at low bit-rates [3]. Hence, improving the efficiency of JPEG compression at low bit-rates is an important issue.

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A large amount of post-processing methods have been proposed to remove blocking effects in JPEG compressed images. A common technique is based on the projection onto convex sets (POCS) algorithm [4-8]. POCS removes blocking artifacts by iterative process, where a constraint set is defined with a prior knowledge about the original image. Defining a proper constraint set has a great influence in the ability of this approach.

The method proposed by Tai et al. uses adaptive filtering to reduce blocking effects [9]. Three different types of filtering modes are employed in this method, according to the amount of activity across block boundaries. The approach proposed by Yeh *et. al.* provides four filter modes to remove the blocking effects in various frequency regions based on region activity analysis [10]

In literature a signal adaptive weighted sum (SAWS) technique is applied on pixels in block boundary to alleviate the blocking artifacts [11]. The weights are adjusted adaptively according to the activities of local areas and directional correlation.

Zhang and Salari proposed an adaptive filter based on neural network to remove blocking effects [12]. In this method a neural network is trained to provide the filter coefficients. Zhang *et. al.* also uses the neural

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network for adaptive filtering to remove blocking effects [2]. In this method, each block of the given image is categorized into one of the three types: plain, edge or texture, according to its statistical characteristics. Then blocking effects are reduced by applying the three trained neural networks on different blocks of the image. According to the results shown in reference [2], this method can partially remove the blocking effects.

Nieves et al. proposed a post-processing method which removes the blocking effects of the image by combining the knowledge extracted from the image domain and the transformed domain [13]. Although this method can efficiently remove the blocking effects, it needs some extra information such as the value of quality factor (QF) about the JPEG compressed image. The method proposed by Jung et al. removes blocking effects based on sparse representation [14]. In this method, a global dictionary is obtained from a set of training images using the K-singular value decomposition (K-SVD) algorithm. Providing a global dictionary from a set of training images may not support all of the test images with blocking effects. In addition, this method requires the value of QF in JPEG compressed image for determining the error threshold value to make use of the dictionary for image deblocking.

Yeh et al. proposed a self-learning based post-processing method via sparse representation [15]. In this method, first an image is decomposed into the low-frequency and high-frequency parts [16-18]. Then the high-frequency part is decomposed into blocking components and non-blocking components by performing dictionary learning and sparse coding. Finally, blocking components are removed from the high-frequency part. This method assumes that blocking effects merely exist in high frequency areas, which is not correct [19]. Hence this method cannot efficiently remove the blocking effects.

In this paper, we have proposed a new single image deblocking via sparse representation. Initially a dictionary is learned from the single blocky image using K-SVD. Then an appropriate value of error threshold for orthogonal matching pursuit (OMP) is automatically estimated without knowing the QF of the JPEG compressed image.

This paper is structured as follows: The JPEG compression algorithm is reviewed in Section 2. Section 3 describes the proposed approach whereas; Section 4 presents the performance evaluation of the proposed method. Finally, the conclusions are drawn in Section 5.

2. JPEG COMPRESSION ALGORITHM

In JPEG compression, once the image blocks were transformed in DCT domain, the quantization process is applied. In the quantization process, each element of DCT coefficient is divided by the corresponding element in the quantization matrix, followed by rounding to the nearest integer value:

$$F = round\left(\frac{D}{W}\right), \tag{1}$$

where D is the DCT coefficients for an 8×8 block and W is the 8×8 quantization matrix. The values in the quantization matrix determine the bit-rate of the JPEG compressed image. The values of quantization matrix increase as the bit-rate decreases. Hence, DCT coefficients are further decreased via quantization, consequently quality of the decoded image is reduced. Indeed, image bit-rate and quality of the decoded image can be estimated for a chosen specific quantization matrix. Table 1 shows the JPEG quantization matrix for JPEG quality factor of 50. In this table, coefficients near to the up-left corner correspond to the lower frequency and coefficients near to the down-right corner correspond to the high frequency. Since, human eye is more sensitive to the low frequency contents than the high frequency ones; elements of the low frequency are smaller than the high frequency in the quantization matrix. Hence, the quantization process will further attenuate the high frequency in comparison with the low frequency contents.

The quality factor in JPEG is in the range of [1, 100], in which *one* results in the lowest bit-rate and the worst quality, whereas *hundred* leads to the highest bit-rate and the best quality. Indeed, the lower QF causes more blocking effects. The quality factor is employed to scale the quantization matrix by a weighting factor S using the following equation:

$$S = \begin{cases} \frac{50}{QF} & if \quad QF < 50 \\ 2 - \frac{QF}{50} & if \quad 50 \le QF < 100 \end{cases} \tag{2}$$

Quantization matrix for different bit-rates of JPEG is obtained as follows:

$$W = S \times W_{50}, \tag{3}$$

where, W_{50} is the JPEG quantization matrix for quality factor of 50.

TABLE 1. The JPEG quantization matrix for quality factor of 50

	Low to high frequency							
Low to high frequency	16	11	10	16	24	40	51	61
	12	12	14	19	26	58	60	55
	14	13	16	24	40	57	69	56
	14	17	22	29	51	87	80	62
	18	22	37	56	68	109	103	77
	24	35	55	64	81	104	113	92
	49	64	78	87	103	121	120	101
	72	92	95	98	112	100	103	99

Finally, an entropy encoder such as Huffman coding or arithmetic coding is used to compress the quantized DCT coefficients.

Figure 1 shows an example of JPEG compressed image with two different QF values. This figure represents that JPEG causes severe blocking effects at low bit-rates.

3. PROPOSED METHOD

Figure 2 exhibits the flowchart of the proposed image deblocking method. In the following, the proposed method is described in details. It is noteworthy that the proposed deblocking method can perform on both gray and color images. Since JPEG algorithm uses ycbcr color mode for compressing the color images, we also use this color mode for image deblocking. We will only concentrate on one color channel, since the proposed method is applied on each color channel.

Sparse representation is an efficient technique which can solve many inverse problems in image processing applications such as denoising and deblocking. In this paper, a post-processing method is proposed for reducing JPEG blocking effects via sparse representation. Sparse representation assumes that each patch of an image can be represented by a linear combination of several atoms in an overcomplete dictionary. The objective function is defined according to the following equation to generate the dictionary:

$$min_{D,\alpha}\|X - D.\alpha\|_{2,}^{2} \quad (4)$$

$$subject\ to \quad \forall i, \|\alpha_i\|_1 \leq S , i = 1,2, \ldots , P$$

where D is the dictionary, X is an $n \times P$ matrix containing P training patches with the length of n pixels, α is a sparse matrix containing P training sparse vectors, α_i is a sparse vector, and S represents sparsity level. This optimization problem can be solved via a dictionary learning algorithm, such as the online dictionary learning [20] and K-SVD [21], where the sparse coding (finding sparse vector) is usually obtained by using OMP [22]. Accordingly, two unknown variables of D and α can be alternatively and progressively approximated. First an initial dictionary is considered, then the initial sparse vector is obtained; accordingly the dictionary and the sparse vector are updated iteratively. Dictionary and sparse vector are updated by K-SVD and OMP respectively. Hence, after a number of iterations, deblocking dictionary is converged. It is noteworthy that K-SVD is a simple and efficient algorithm which generates atoms for dictionary that fits with training patches well. Details of dictionary generation using K-SVD are described in Algorithm 1 [14].

In this paper, for training the dictionary, we consider 2000 training patches with size of 10×10 from the single blocky image, 256 atoms for dictionary and 40 iteration numbers for K-SVD. These values were obtained empirically. Figure 3 shows an example of the initial dictionary and the learned dictionary for a blocky image. Initial dictionary is considered according to DCT basis functions and is used in the initialization for the training algorithms.

(a) Original image (b) JPEG compressed image with QF=50 (c) JPEG compressed image with QF=5

Figure 1. Example of an image with two different quality factors of JPEG

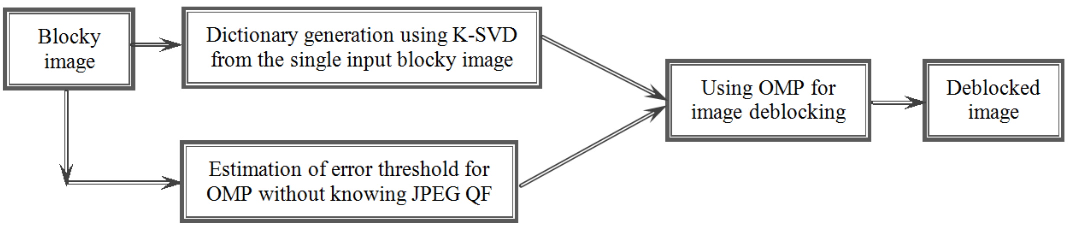


Figure 2. Flowchart of the proposed deblocking method

Algorithm1. K-SVD algorithm for dictionary generation [14].

Input: $X = [x_1, x_2, \dots, x_p]$, where X is $n \times P$ matrix containing P training patches with the length of n pixels

Output: D, Deblocking dictionary

1- Initialize D

2- **repeat**

3- Compute α_i using OMP for $i = 1,2, \dots, P$.

4- Update each atom of dictionary d_k, $k = 1,2, \dots, K$ where K is the number of atoms in dictionary

4-1- Compute $w_j = \{p | 1 \leq p \leq P, \alpha_j^T(p) \neq 0\}, 1 \leq j \leq K$.

4-2- Compute $H_j = X - \sum_{i \neq j} d_i \alpha_i$.

4-3- Restrict H_j by choosing only the columns corresponding to those elements that initially used d_k and named the result H_j^R.

4-4- Apply SVD decomposition $H_j^R = U \Delta V^T$ and update $d_k = u_1$, $\alpha_k^R = \Delta(1,1) v_1$.

Where $\Delta(1,1)$, u_1 and v_1 are the largest singular value and the corresponding left and right singular vectors of E_k^R respectively.

5- **until** N times

Trained dictionary was produced using the K-SVD from the single blocky image in Figure 3 (a). Each atom of the dictionary is an 8×8 pixel image.

After generating the dictionary, deblocked image can be obtained using this dictionary. The optimization function for image deblocking can be defined as follows:

$$min_\alpha \|\alpha\|_1, \quad subject\ to\ \ \|Y - D.\alpha\|_2 \leq T, \tag{5}$$

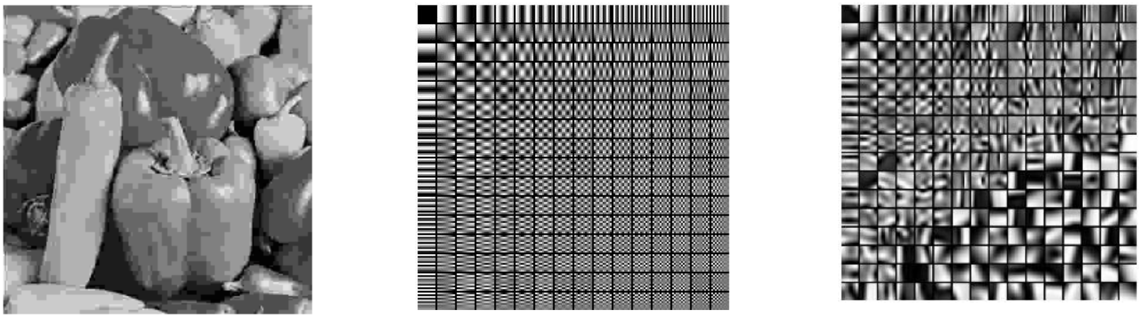
where Y is the blocky image, T is an error threshold for OMP, D is the deblocking dictionary, and α contains sparse coefficients. Unpleasant artifacts can be removed via optimizing the equation in (5). Determining the appropriate value for variable T has an important role in deblocking result of OMP. The method in [14] estimates this value using the QF of JPEG, which is unknown. Hence, this method can only be performed on JPEG compressed image with a known QF.

In this paper, we consider that the threshold value is related to the amount of blockiness degradation of the image. The amount of blockiness degradation can be determined using a no-reference image quality assessment. Asadi et al. introduced a no-reference image quality metric for JPEG compressed images without knowing any prior knowledge about the value of QF [23]. This metric represents the amount of blockiness degradation of the JPEG compressed image with a score within (0, 1]. The score close to zero represents the best image quality and score one or close to one represents the worst image quality. Accordingly, we estimated the error threshold value using this metric as follows:

$$T = (200^\wedge M) \times 2, \tag{6}$$

where M represents the amount of blockiness degradation. The above equation represents that the value of T has direct relation with the amount of JPEG blockiness degradation. The value of T increases as the blockiness of the image get worse.

The proposed metric in reference [23] uses the DCT coefficient values to score image quality in terms of blocking artifacts. An image may have uniform and non-uniform blocks, which are respectively associated with the low and high frequency information. Once an image is compressed using JPEG, inherent non-uniform blocks may become uniform due to quantization, whilst inherent uniform blocks stay uniform. In this metric for assessing the quality of an image, firstly, inherent non-uniform blocks are distinguished from inherent uniform blocks by using the sharpness map [24]. If the DCT coefficients of the inherent non-uniform blocks are not significant, it indicates that the original block was quantized. Hence, the DCT coefficients of the inherent non-uniform blocks are used to assess the image quality. Algorithm 2 represents the pseudo code of the proposed deblocking method.



(a) blocky image (b) initial dictionary (based on DCT basis functions) (c) trained dictionary using the blocky image (a)

Figure 3. An example of the trained dictionary for a blocky image

Algorithm 2. Pseudo code of the proposed deblocking method.

1: Input the blocky image.

2: Compute the amount of blockiness degradation (M) of the input blocky image according to the technique introduced in [23].

3: Estimate the error threshold for OMP using the blockiness degradation (M).

4: Generate the dictionary using K-SVD from the single input blocky image.

5: Use OMP for image deblocking by the learned dictionary and the error thereshold.

4. EXPERIMENTAL RESULTS

The proposed method was evaluated on various images and its performance was compared with the performance of a number of well-known methods [2, 13, 15]. In order to evaluate the performance of the proposed method, we used both the PSNR and bpp measures. PSNR is a quantitative measure which is defined as follows:

$$PSNR = 10\ log_{10} \frac{255^2}{1/(m\times n)\left(\sum_{i=1}^{m}\sum_{j=1}^{n}(I(i,j)-\hat{I}(i,j))^2\right)}, \quad (7)$$

where, I is the original image, $\hat{I}$ is the post-processed image, m and n represent the image width and high respectively. The higher value for PSNR indicates a superior similarity between the original image and the post-processed one.

The bpp criterion specifies the number of bits used to indicate a single pixel in an image. Consequently, the lower value of bpp is preferred. This measure is defined as follows:

$$bpp = \frac{H}{m\times n}, \quad (8)$$

where H is the image size in bits, m and n represent the image width and height respectively. Figures 4-6 illustrate three instance results of the proposed method in comparison with JPEG and the three well-known image deblocking methods. As mentioned before, the existing method in [13] needs QF of JPEG compressed image for image deblocking. As can be seen, the proposed method achieves a higher PSNR than those methods at the same bpp, and the visual qualities are greatly improved. Also, blocking artifacts are remarkably eliminated whilst edges and image details are efficiently preserved in the proposed method. It is noteworthy that, since most of the existing methods do not provide the results on specified databases, we compared the proposed method with the state-of-the-art on different images reported in their papers.

Table 2 shows the performance of the proposed method and the method proposed in [2] on test images in terms of both bpp and PSNR values. In this table, the best results are indicated in boldface. The results represent that the proposed deblocking method obtains the highest PSNR value.

(a) original image

(b) JPEG (PSNR=24.2976)

(c) method introduced in [2] (PSNR=25.2849)

(d) proposed method (PSNR=26.6066)

Figure 4. Example 1: comparison results of removing blocking effects on peppers for QF=2 (bpp=0.1369)

(a) original image

(b) JPEG (PSNR=29.999)

(c) method introduced in [15] (PSNR=31.2514)

(d) proposed method (PSNR=31.3694)

Figure 5. Example 2: comparison results of removing blocking effects on Lena for QF=10 (bpp=0.2919)

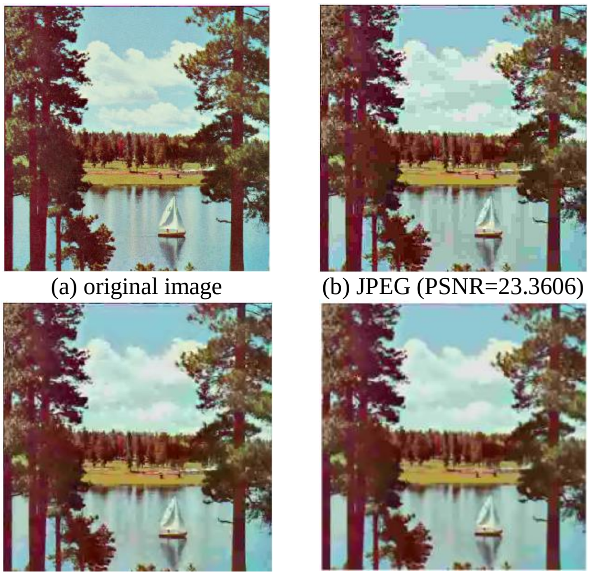


Figure 6. Example 3: comparison results of removing blocking effects on Lake QF=7 (bpp=0.3116)

TABLE 2. The comparison results of the proposed deblocking method with the one introduced in [2].

	bpp	JPEG (PSNR)	Proposed method (PSNR)	(PSNR) [2]
Lena	0.1729	27. 3283	**29.0164**	28.4364
Bills face	0.0454	24.7089	**27.0035**	24.7088
Forman	0.0901	28. 1594	**29.8720**	27.4000
Claire	0.1917	30. 6244	**31.7999**	30.1278
Peppers	0.1369	24. 2976	**26.6056**	25.2849
Elaine	0.1557	27. 5018	**29.0268**	28.1461

Furthermore, we applied the proposed method on 24 color images from Kodak database and compared the results with JPEG, and the method in [13]. Figure 7 shows the comparison results in terms of the average PSNR versus three different QFs. As can be seen, the proposed method produces better PSNR values than both JPEG and the method in [13] at different QF. As mentioned before, the method in [13] needs the QF for attenuating the blocking effects whilst the proposed method needs no extra information.

5. CONCLUSIONS

In this paper, we have proposed a new deblocking method for JPEG compressed image at low bit-rates. In this method, a self-learning sparse representation is used for image deblocking.

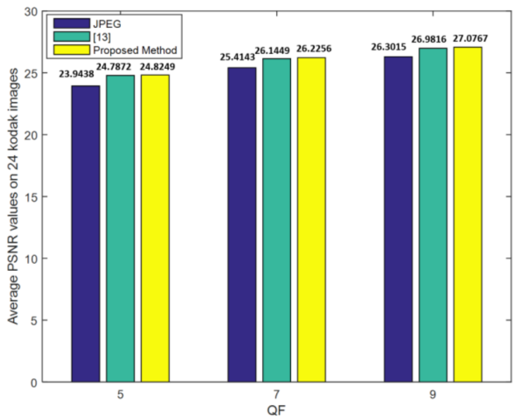


Figure 7. The performance evaluation of three methods on the Kodak database in terms of PSNR in image deblocking

The dictionary learning of the proposed method is self-contained; it means no extra training images are needed. Moreover, we provided an automatic error threshold estimation method to make use of the dictionary in image deblocking without knowing the quality factor of the JPEG compressed image. The proposed deblocking method was evaluated on Kodak database and compared with some effective deblocking methods. The results showed that the proposed method outperforms the existing deblocking methods for image deblocking in terms of PSNR and visual quality.

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چکیده

JPEG یکی از پر کاربردترین روش‌های فشرده‌سازی تصویر است، اما این روش منجر به اثرات بلوکی آزاردهنده در نرخ-های بیت پایین می‌شود. نمایش تنک یک تکنیک کارآمد است که می‌تواند بسیاری از مسائل معکوس را در کاربردهای پردازش تصویر همچون حذف نویز و حذف اثر بلوکی حل نماید. در این مقاله، یک روش پس‌پردازش برای کاهش اثرات بلوکی با نمایش تنک پیشنهاد شده است. در این روش، یک واژه‌نامه با تک تصویر بلوکی ورودی با استفاده از K-SVD آموزش داده می‌شود. نیازی به دانستن دانش پیشین در مورد اثرات بلوکی نمی‌باشد. نتایج تجربی بر روی تصاویر مختلف نشان داد که پس‌پردازش پیشنهای به صورت کارآمد می‌تواند اثرات بلوکی را در نرخ بیت پایین حذف نماید و برتر از روش‌های موجود است.

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