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Effect of Anti-Forensics and Dic.TV Method for Reducing Artifact in JPEG Decompression

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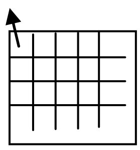
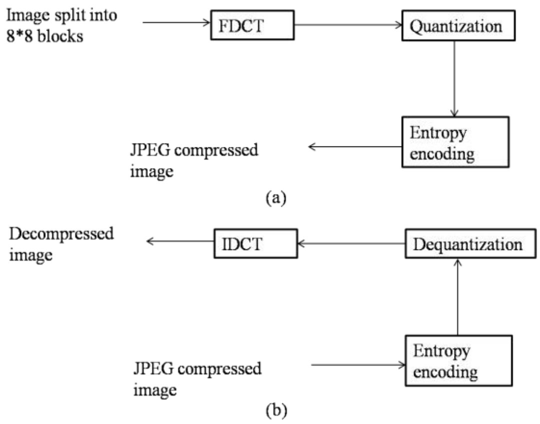
Abstract: The JPEG compression method is an efficient compression scheme used for image compression with good compression ratio. However, the decompressed image contains some artifacts, such as quantization artifact, blocking artifact, Gibbs artifact, etc. The presence of noise in the compressed image also affects the quality of the reconstructed image. JPEG compression provides efficient compression with good compression ratio. In this paper, proposed a combination of two artifacts reducing techniques for reducing artifacts in JPEG decompressed images. The first is a Dic. TV method, which involves the sparse representation of the compressed image over a learned dictionary and a total variation regularization for restoring the original image. The second is an anti-forensic operation for removing the quantization artifact.

***Keywords**: JPEG, Decompression, Learned Dictionary, K SVD, Total variation, Anti-Forensics.*

1. Introduction

The JPEG compression [5], [6] is an efficient compression method. It is done in three steps. In the first step decompose the original image into 8×8 blocks and taking the DCT of each block. In the second step the DCT coefficients are uniformly quantized. In the third step the quantized image is given to an entropy encoder which encode the quantized values to generate the compressed image. The JPEG decompression can also be done in three steps. It includes decoding, dequantization and inverse DCT to each block. The JPEG compression and Decompression procedures are shown in fig. 1.





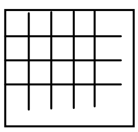


Figure 1. (a) JPEG compression; (b) JPEG decompression

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Most of the information loss in JPEG compression is taking place in the quantization step. This loss of information is cause of artifacts. Because of these artifacts the reconstructed or decompressed is not exactly same as that of the original image. The main artifact in the quantization process is the quantization artifact. The objective of this paper is to study the effect of combining two artifact reducing techniques in reducing artifacts for decompressed images. They are Dic. TV method for noise removal and anti-forensic operation for removing quantization artifact. Fig2 (a) shows the original image and fig.2 (b) shows the corresponding JPEG compressed image.

2. Previous Work

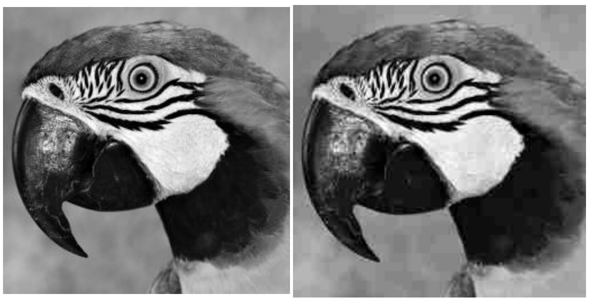
Reducing Artifact via a Learned Dictionary

Huibin Chang, Michael K. Ng, and Tieyong Zeng [1] proposed a novel artifact reducing approach for JPEG Decompression via sparse and redundant representations via a learned dictionary. Also, proposed an efficient two step algorithm. In this work, developed a reducing artifact model for reconstructing JPEG decompressed images in the discrete setting:

$$\min_{\{\{\gamma_{i,j}\},D,u\}} \sum_{(i,j)\epsilon P} \left(\frac{1}{2}\left\|R_{i,j}u - D\gamma_{i,j}\right\|_2^2 + \mu_{i,j}\left\|\gamma_{i,j}\right\|_o\right) + \lambda T\nu(u) + U(u) \tag{1}$$

where D is a dictionary of size m^2-by-c attached to the restored image u with atoms in the dictionary; $R_{,,j}$ is the sampling matrix of size m^2-by- N to construct a patch for the part of u; $\gamma_{,,j}$ is a vector of size c -by-1 containing the encoding coefficients for the patch of u represented in the dictionary; $P = \{1,2,\dots,n-m+1\}^2$ denotes the index set of different patches of u; $\|.\|_2$ denotes the Euclidean norm of a vector; denotes $\left\|\gamma_{i,j}\right\|_o$ the number of non-zero elements; The parameter is a positive parameter of the data fitting term, and $\mu_{i\ ,j}$ is the positive patch-specific weight.

$$T\nu(u) = \sum_{l=1}^{N} \sqrt{([\nabla \mathrm{u_x}]_l)^2 + ([\nabla u_y]_l)^2} \tag{2}$$



(a) (b)

Figure 2. (a) Input image; (b) JPEG compressed image

where ∇ is the discrete gradient operator, $([\nabla \mathrm{u_x}]_l$ and $([\nabla u_y]_l$ are the x-derivative and y-derivative values at the l-th pixel ($1 \le l \le$ N) discretized by forward difference schemes;

$$U(u) = \begin{cases} 0, & if\ u \in \cup \\ +\infty, & otherwise \end{cases} \tag{3}$$

For solving the above model, an efficient two step algorithm was used. First a dictionary is learned using the K SVD algorithm. K SVD is a two step iterative method. In the first step of each iteration a sparse coding is done, where an orthonormal matching pursuit (OMP) algorithm is used for updating the encoding coefficients. In the second step, the dictionary is updated using SVD. Finally, the image is restored using total variation regularization method.

Anti-Forensics for Removing Quantization Artifact

In this technique [2], a sufficient amount of noise is added to each DCT coefficient for the removal of quantization artifact. This makes the values of each DCT coefficient no longer clustered around inter multiples of the quantization matrix Q. The choice of noise distribution is important. Distortions may be introduced if the noise added is more and if it is not sufficient artifacts will remain in the resultant image. There are two steps for doing this in a proper way. The is the estimation of the unquantized DCT coefficient distribution and the next is the additive noise distribution.

3. Proposed System

In this method, proposed a combination of KSVD, total variation regularization and anti-forensic methods for reducing artifacts in JPEG compression and thereby increasing the quality of the reconstructed image. The original input is decomposed into 8×8 blocks. To convert each 8×8 block of the original input image into its frequency domain, define a DCT matrix A of size N×N. It is then quantized using a quantization matrix M_q. At this stage of JPEG compression, some errors may be introduced. For reducing this error and to reconstruct image, an artifact reducing model is developed:

$$\min_{\{\{\alpha_{i,j}\},D,u\}} \sum_{(i,j)\epsilon P} \left(\frac{1}{2}\left\|R_{i,j}u - D\alpha_{i,j}\right\|_2^2 + \mu_{i,j}\left\|\alpha_{i,j}\right\|_o\right) + \lambda Tv(u) + U(u) \quad (4)$$

After solving the above model, an anti-forensics method is used for reducing the remaining quantization artifacts.

In this paper, an efficient two step algorithm is employed for solving the unknowns: $\{\alpha_{,,j}\}$, D, u . The algorithm is given as:

1.Initialize the parameters λ, $\{\alpha_{i,j}\}$, and the JPEG compressed image u'.
2. Solve the following to determine $\{\alpha_{,,j}\}$, D, u
.

$$(\alpha_{i,j}{}^{*}D^{*}) = arg \min_{\{\{\alpha_{i,j}\},D,u\}} \sum_{(i,j)\epsilon P} \left(\frac{1}{2}\left\|R_{i,j}u - D\alpha_{i,j}\right\|_2^2 + \mu_{i,j}\left\|\alpha_{i,j}\right\|_o\right) \quad (5)$$

$$\min_{u\epsilon \cup} \lambda Tv(u) + \sum_{(i,j)\epsilon P} \left(\frac{1}{2}\left\|R_{i,j}u - D\alpha_{i,j}\right\|_2^2\right) \quad (6)$$

K-SVD algorithm [3] can be used to solve the model (5). K-SVD is a two step iterative algorithm, where alternatively updating the encoding coefficients and the dictionary. An orthonormal matching pursuit (OMP) [5], [13] algorithm can be used to update the encoding coefficients. After updating the encoding coefficients, dictionary D is updated using SVD. To solve the model (6) a total variation regularization (TV) [4] [1] method is used.

Finally, a noise free image is produced. But some quantization artifacts may remain in the reconstructed image.This artifact is introduced due to the quantization and dequantization operations. It will affect the texture and quality of the reconstructed image. In order to reduce this artifact an anti-forensics techniques [2] is presented. In this technique, removes the quantization artifact by the proper addition of noise to the DCT coefficients of the image.For doing this, there are two steps

1. Estimation of the unquantized discrete cosine transform coefficient distribution
2. Addition of noise

Let Y be the anti-forensically modified DCT coefficient then,

$$Y = u + \eta \quad (7)$$

where u is the image affected by quantization artifact and η is the additive noise .The distribution of η depends on the value of Y.

The noise distribution for quantized DCT coefficients is given by

$$P(X_i = x) = \begin{cases} -\frac{1}{\lambda_i} * sgn(x) * \log\big(C(1-2|x|)\big) + e^{-\lambda_i\left(\frac{M_q}{2}\right)}, \\ \qquad x = 0 \\ -\frac{1}{\lambda_i} * \log\Big(1 - \big(1 - e^{-\lambda_i M_q}\big)\Big) * x - \left(\frac{M_q}{2}\right), \\ \qquad x > 0 \end{cases} \tag{8}$$

where $a_0 = 1 - e^{-\beta_{ML}\frac{M_q}{2}}$; $\beta_{ML} = -\frac{2}{M_q}\ln(\rho)$

$$\rho = \frac{-A_0 M_q}{2\eta M_q + 4S} + \frac{\sqrt{A_0{}^2 M_q{}^2 - (2A_1 M_q - 4S)(2AM_q + 4S)}}{2AM + 4S} \tag{9}$$

where S=$\sum_{k=1}^{A}|u_k|$, A is the total number of quantized coefficients, A_0 is the number of coefficients with value zero, A_1 is the number of coefficients with non zero values.
Because no general model accurately represents the DC coefficient distribution, we add noise with the distribution

$$P(X_i = x) = M_q * x - (\tfrac{M_q}{2}) \tag{10}$$

By choosing the noise distributions as (8) and (10), the distributions of anti-forensically modified DCT coefficients will match the distribution of unmodified DCT coefficients [2]. So in sufficient addition of noise to the quantized DCT coefficients can effectively remove the quantization artifact to get a good quality image.

By combining the Dic. TV method and the anti-forensics technique can effectively produce an artifact free decompressed image.

6. Results and Discussion

In the Dic. TV method the image patch of size 6×6 is taken and the number of atoms in the dictionary is chosen as 108=6^2 ×3 (where 3 is the redundancy factor which is chosen empirically). The value of q is in between 0 and 100, quantization matrix for M_q for q=50 is

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

The quality of the decompressed image can be evaluated by considering the PSNR (peak signal to noise ratio) value and SSIM metric. The average SSIM index, is utilized to measure the overall image quality. The larger the value is, the better the restoration result, we have. The PSNR value is given by:

$$PSNR(u,u') = 10log_{10}\left(\frac{255^2}{\sqrt{\sum_{1\le i\le N}\frac{(|u|_i - |u'|_i)^2}{N}}}\right)$$

Assume that u(i) and u'(i) are sub-images of size 11×11 centered at the i-th pixel location of two images u and u' respectively and the local SSIM index is given by

$$SSIM_l\big(u(i),u'(i)\big) = \frac{\big[2\mu\big(u(i)\big)\mu\big(u'(i)\big)+b_1\big]\big[2\sigma\big(u(i)u'(i)\big)+b_2\big]}{\big[\mu^2\big(u(i)\big)+\mu^2\big(u'(i)\big)+b_1\big]\big[\sigma^2\big(u(i)\big)+\sigma^2\big(u'(i)\big)+b_2\big]}$$

where $\mu\big(u(i)\big)$ and $\mu\big(u'(i)\big)$ represents the mean values of u (i) and u'(i), $\sigma^2\big(u(i)\big)$ and $\sigma^2\big(u'(i)\big)$ are the corresponding variances, the covariance is given by $\sigma\big(u(i)u'(i)\big)$ and b_1, b_2 are constants which depend on the dynamic range of u and u'. The average SSIM index is given by

$$\mathrm{SSIM}(u,u') = \frac{1}{N}\sum_{i=1}^{N}\mathrm{SSIM_l}\big(u(i),u'(i)\big)$$

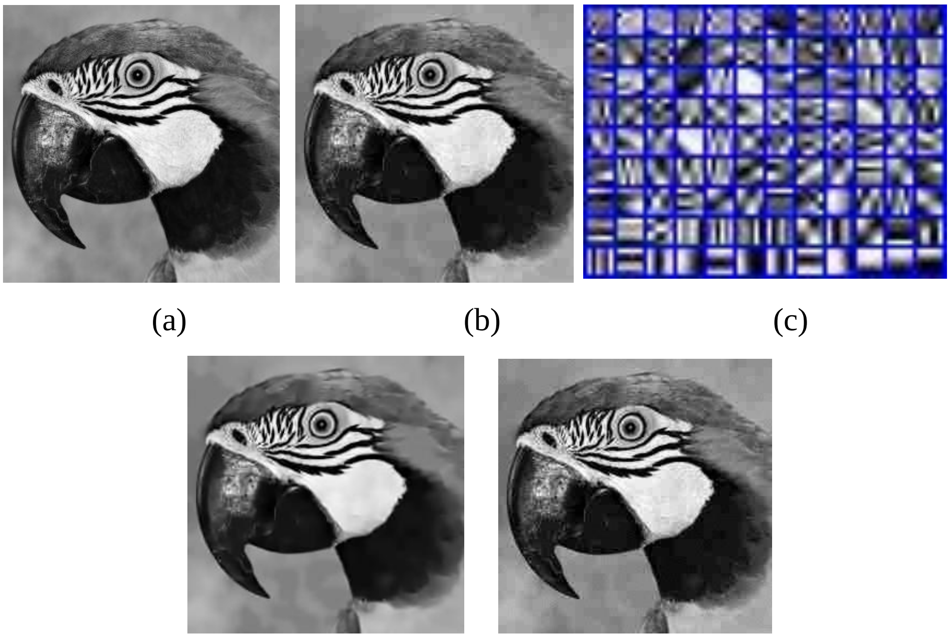
The PSNR and SSIM values for different images with q value 10,50/3,25 are shown in the table.

q	**Name**		**Dic. TV**	**Dic. TV and Anti-Forensics**
10	Cameraman	PSNR SSIM	35.0729 0.894016	37.2141 0.928128
	Parrot	PSNR SSIM	34.0669 0.866441	35.7349 0.963961
	Lena	PSNR SSIM	35.0475 0.87107	37.7953 0.952257
	House	PSNR SSIM	34.579 0.845544	40.1865 0.931716
50/3	Cameraman	PSNR SSIM	34.9176 0.903956	36.5383 0.912573
	Parrot	PSNR SSIM	34.6313 0.886574	36.0822 0.962302
	Lena	PSNR SSIM	35.8396 0.888811	38.4313 0.95691
	House	PSNR SSIM	35.2818 0.844259	40.0246 0.942548
	Cameraman	PSNR SSIM	34.8929 0.90524	35.6511 0.88639

25	Parrot	PSNR SSIM	34.7265 0.888722	35.5891 0.956726
	Lena	PSNR SSIM	36.113 0.89482	38.2755 0.95231
	House	PSNR SSIM	35.5335 0.84527	40.1062 0.933613
	Average	PSNR SSIM	35.0585 0.87789	37.6357 0.939952

Table 1. PSNR and SSIM values for q=10, 50/3,25

From the table it clear that the PSNR and SSIM values are improved for the proposed method than the Dic. TV method.



(a) (b) (c)

(d) (e)

Figure 3. (a) Original image (b) JPEG compressed image with artifacts (c) Learned dictionary, (d) Decompressed image by Dic TV method (e) Decompressed image by Dic.

TV and Anti-forensic method from the results it can be seen that an artifact free image can be obtained using the combination of Div. TV method and the anti-forensic operation. So that this combination is very effective in reducing artifacts for JPEG decompression..

6. Conclusion

In this paper, proposed a combination of Dic. TV and anti-forensics methods for reducing artifacts in JPEG decompression. Dic. TV method removes the noise and the anti-forensic operation removes the DCT coefficient quantization artifact. The dictionary learning is performed by the K-SVD algorithm and the restored image is obtained using TV method. The anti-forensic operation is done by adding a proper amount of noise to quantized DCT coefficients.

The output result obtained is an artifact free image. The combination of these methods outperforms the total variation and weighted total variation methods.

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