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Approaches for Reducing Artifacts in JPEG Decompression: A Survey

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Abstract: JPEG compression scheme is one of the most popular compression techniques which are used frequently in the real world for compression. This is used to reduce the memory consumption while forwarding the image from one place to another place. In this technique, the quality of images is reduced compared to original image after decompression especially if the compression ratio is high. There are many methods that reduce the artifacts produced by JPEG compression. In this paper, different techniques used to reduce the visible artifacts in compressed and decompressed domains have been reviewed. It has been observed a strategy with a combination of learned dictionary along with total variation regularization is an efficient method for reducing artifacts in JPEG. But it has been analyzed this method is quite computationally demanding.

Keywords: JPEG, DCT, Mean Field Annealing, Post Processing, Total Variation, Dictionary Learning, K-SVD.

I. INTRODUCTION

Image processing is the method to improve the original images obtained from camera or any other source. Many image processing techniques can be used. One of the processing techniques, image compression is used to reduce the amount of data required to represent an image. Compression can be exercised by removing information-theoretic redundancies from the original image such that the original image can be recovered exactly from the compressed image as in lossless compression methods or by removing psycho-visual redundancies such that compressed image visually approximates the original image as in lossy compression methods. Compressing an image is significantly different than compressing raw binary data. There are different ways to compress an images, lossless compression and lossy compression. A lossless technique means that the restored data file is identical to the original. Lossy compression is based the concept that all real world measurements inherently contain a certain amount of noise. The additional noise is occurred when the changes made to the image but it does not cause any harm. Overcome by reducing the visible artifacts to improving the quality of JPEG decompressed images.

Over the long history of image compression, several standards have been established aiming to accomplish application specific requirements, satisfy computational complexity criterion and visual quality constraints. Despite the increased choices of image compression standards, doubtlessly, JPEG, a member of lossy compression standards family, is the most popular image compression standard among all others. But the main problem is that certain visible artifacts such as blocking, ringing and staircase artifacts that appear at the time of quantization. Compression artifact is a noticeable distortion of media (image, audio, video) caused by the application of lossy data compression. It is a particular class of data error that is usually the consequence of quantization in lossy data compression. The compressed images, several types of artifacts can appear namely ringing, blocking, contouring, posterizing, staircase noise, etc. Fig 1 shows the JPEG compression and decompression standards.

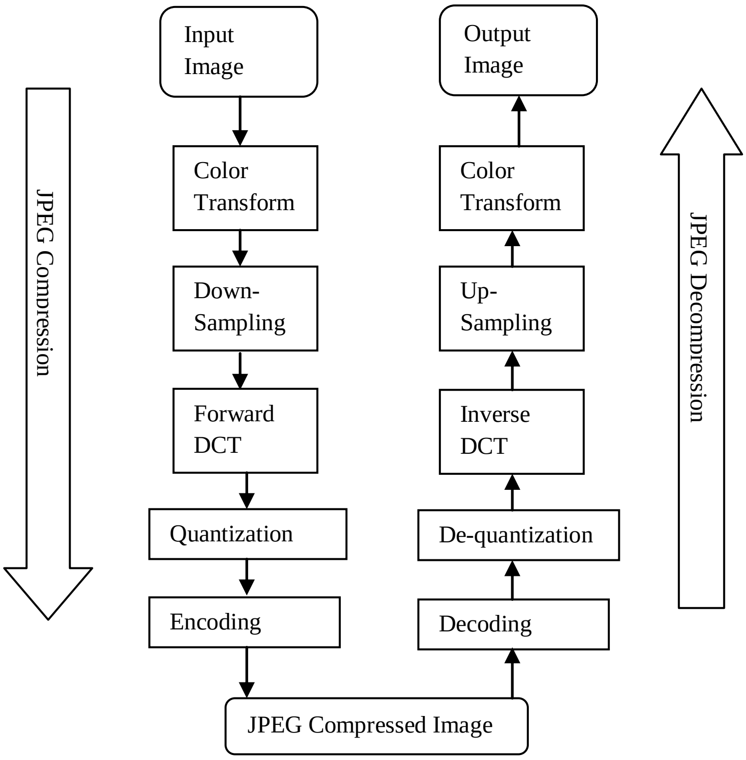

Fig 1: JPEG Compression and Decompression [6]

In this standard, source color images are transformed from RGB into a luminance/chrominance color space. Then color images are down-sampled by creating low-resolution pixels from the original ones. Then the pixels of each component are organized in groups of 8×8 pixels are compressed separately. Next the DCT is applied to each data unit to create an 8×8 map of frequency components. Then each of the 64 frequency components in a data unit are divided by a separate number called its quantization coefficient, and then rounded to an integer. And finally the 64 quantized frequency coefficients of each data unit are encoded using a combination of RLE and Huffman coding. Since it is basically a block-based process, none of the inter-block correlation is exploited during the compression and therefore it causes visible discontinuities among adjacent blocks. This blocking effect is generally considered to be the most noticeable artifact in the reconstructed image. The decompression for JPEG images is a reverse process of encoder. The procedure involves lossless decoding, de-quantization and computing the inverse DCT to each block.

By using process such as aberrations from camera and visible compression artifacts, the image quality is deteriorated, that would like to remove. In JPEG compression, decoded images exhibit block artifacts (discontinuities that appear between the boundaries of the blocks) and ringing artifacts. Despite extensive research, reducing these artifacts in an effective manner still remains challenging. It performs simple image processing techniques to clean out ringing and blocking artifacts from these regions. Fig 2. (a) shows decompressed image with visible artifacts and Fig 2. (b) shows artifact-free image.

(a) (b)

Fig. 2 (a) Decompressed image with visible artifacts; (b) Artifact-free image.

II. BACKGROUND

JPEG compressed images contains ringing and blocking artifacts, which can be offensive to the viewer above certain compression ratios. The blocking is more visible in natural images while ringing is more dominant around textual regions.

Blocking Artifacts: caused by coarse quantization of low-frequency DCT coefficients yielding decompressed image look like a mosaic at smooth regions.

Ringing Artifacts: caused by coarse quantization of high-frequency DCT coefficients making the decompressed image exhibit noisy patterns known as ringing or mosquito noise near the edges.

The quality of compressed image can be evaluated qualitatively and quantitatively. PSNR and SSIM are usually used by quantitative evaluation of image quality.

PSNR: PSNR is defined as a ratio between maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. In image compression Signal is the pristine data or image, and noise is the error introduced by compression. It is expressed in terms of logarithmic decibel scale.

$$PSNR = 20\ \log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

Here, MAX_f is the maximum possible pixel value of the image. MSE (Mean Squared Error) is the cumulative squared error between the compressed and the original image.

SSIM: The Structural Similarity index (SSIM) is a method for checking the resemblance between two images. SSIM considers image degradation as perceived change in structural detail.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c1)(2\mu_{xy} + c2)}{\left(\mu^2{}_x + \mu^2{}_y + c1\right)\left(\sigma^2{}_x + \sigma^2{}_y + c2\right)}$$

Where, μ_x the average of x; μ_y the average of y; σ_x^2 the variance of x; σ_y^2 the variance of y; σ_{xy} the covariance of x and y; $c_1=(k_1L)^2$, $c_2=(k_2L)^2$ two variables to stabilize the division with weak denominator; L the dynamic range of the pixel-values (typically this is $2^{\#bits\ per\ pixel}-1$); $k_1=0.01$ and $k_2=0.03$ by default.

Learned Dictionary: The information about the image restoration will be present in the dictionary. And which is based on the images will be restored into its pristine form by removing the noises present in that image.

Dictionary Learning Algorithm:

1. Parameters definition: In this step define the dictionary learning algorithm parameters: level of sparsity and dictionary size.
2. Create initial dictionary: An initial dictionary must be defined, either by choosing spectral responses from the training set as dictionary elements or some random dictionary.
3. Sparsity coding stage: To measure the sparse coefficients matrix by using one of the sparse coding algorithms.
4. Dictionary update stage: In this step update the dictionary using the generated new sparse coefficients matrix by applying one of the dictionary update algorithms.
5. Repeat: Repeat the main loop until reaching an error limit as predefined by the user.
6. Output: The process output is a learned dictionary and a sparse coefficients matrix.

III. LITERATURE SURVEY

In this survey, different techniques used to reduce the visible artifacts in compressed and decompressed domains have been reviewed.

T. Ozcelik, J. Brailean, and A. Katsaggelos [1] proposed a mean field annealing method to reduce the unwanted degradations such as blocking, ringing and mosquito artifacts. To reduce artifacts while keeping the obligatory detail present in the pristine image. Proposed technique makes utilization of a priori information about the pristine image through a non-stationary guass-markov model. A maximum a posteriori (MAP) estimate is getting iteratively utilizing mean field annealing. The quality to the image is preserved by projecting the image onto a constraint set defined by the quantizer at each iteration. It solves an estimation quandary predicated on the available bit stream and prior cognizance about the source image. Most decoders undo the operations performed by the encoder. Decoder is designed so that it solves an estimation quandary then amended reconstructed results with reduced artifacts can be obtained or equipollently higher compression rates can be achieved for an acceptable quality reconstructed image. The estimation quandary to be solved is that of engendering the best estimate, according to an optimally criterion of the source image predicated on the available bit stream and any erudition available about the source image. In this work, the coupled Gauss Markov (CGM) method used to model the intensity field. A CGM model consists of two layers, a lower layer, or line process, which is utilized to represent the discontinuities of the arbitrary field and an upper layer which describes the observed intensity values. In contrast to the CGM models which have been developed for use in image recuperation and kineticism estimation.

M.-Y. Shen and C.-C. J. Kuo [2] proposed blocking artifacts removal by a hybrid post-processing method. Most compression algorithms yield visually annoying artifacts that highly degrade the perceptual quality of image and video data. Post-processing techniques provide one attractive solution to achieve high bit rate reduction while maintaining the best possible perceptual quality. More information contained in the source signal requires more bits for representation. When compression at the same bit rate, image with more details usually degrade more than those with fewer details. Lower bit rate, more severe the coding artifacts due to loss of information. Blockiness in flat area and ringing along object edges. Two strategies to reduce compression artifact are Preprocessing (Speech & Audio) and Post-processing (Still images). Most post processing algorithm reduces coding artifacts resulting from block DCT are Image Enhancement, Image restoration. A new hybrid method that demonstrates an excellent post processing method. The hybrid post-processing system consists of classification, de-blocking, de-ringing and quantization constraint.

K. Bredies and M. Hollery [3] proposed a novel method for artifact-free reconstruction of decompressed images. In lossy compression, a given JPEG compressed object does not provide exact detail about the pristine source image. But define a convex set of possible source images. Based on given data and minimal total generalized variation (TGV) of second order to re-builds an image. This functional is well-suited for images as it is aware of smooth regions and both edges. The minimization dismay blocking and ringing artifacts which are typical for JPEG compressed images. It not only yields a greater approximation of the pristine image compared to standard decompression. But this method achieve high visual quality image, existing similar variational approaches using different image models such as the total variation. The second order TGV functional is provides a good balance between achieved image quality and computational time. This improvement in the step from order one to order two. Where order one corresponds to total variation regularization, is visually most noticeable. Generalizations to higher orders, however, seem to be possible and might lead to more improvements. Among the continuous formulation, here to present a discretized model and an efficient solution strategy for the resulting finite-dimensional minimization problem. Moreover, it addresses and discusses computation times of CPU and GPU based parallel implementations.

Michal Aharon, Michael Elad, and Alfred Bruckstein[4], proposed sparsity and over completeness concepts (together or separately). And include regularization compression, in reverse problems and feature extraction. The effectiveness of the JPEG2000 standard can be attributed to the sparsity of the wavelet coefficients of natural images. In de-noising, wavelet methods and shift-invariant variations that exploit over complete representation are among the most effective known algorithms for this task. Sparsity and over completeness have been successfully used for dynamic range compression in images, separation of texture and cartoon content in images, inpainting, and more. Extraction of the sparsest representation is a hard problem that has been extensively investigated in the past few years. In this work, address the issue of designing the proper dictionary in order to better fit the sparsity model imposed. An over complete dictionary that leads to sparse representations can either be chosen as a pre-specified set of functions or designed by adapting its content to fit a given set of signal examples. A pre-specified transform matrix is appealing because it is easier. Also, in many cases it leads to simple and fast algorithms for the evaluation of the sparse representation. This is indeed the case for over complete wavelets, contourlets, curvelets, steerable wavelet filters, short-time and Fourier transforms. Preference is typically given to tight frames that can easily be pseudo inverted. The success of such dictionaries in applications depends on how suitable they are to sparsely describe the signals. In learned dictionary, the details about the image restoration will be present based on which images will be restored into its original form by eliminating the noises present in that image.

Chang, Huibin and Ng, Michael K and Zeng, Tieyong [5] proposed reducing artifacts in JPEG decompression via a learned dictionary. This novel approach is introduced for reducing the artifacts that are created while JPEG decompression. The decompression for JPEG images is also very simple. The procedure involves lossless decoding, de-quantization and computing the inverse DCT to each block. The learned dictionary model is used to restore the original image after decompression. The dictionary learning is done in this method via K-SVD method. K-SVD de-noising method, which assumes that each image patch can be represented sparsely using a linear combination of the atoms from a special chosen dictionary. Specifically, it is “sparse” on the sense that Y = DX with the sparse coefficient matrix, where D is the dictionary, and the matrix consists of all the image patches selected from the given image rewritten as a column vector. In order to remove some noise from with pixels of size n * n, which is rewritten as column vector $f \in R^N$ using the lexicographical ordering, the K-SVD de-noising model was given

$$\min_{\{\gamma_{i,j}\},D,u} \lambda \| f - u \|^2 + \frac{1}{2} \sum_{(i,j)\in P} (\| D_{\gamma_{i,j}} - R_{i,j} u \|^2 + \mu_{i,j} \| \gamma_{i,j} \| 0)$$

to generate a learned dictionary $D \in R^{m2*c}$ and the recovered result u. D is a dictionary of size m^2-by-c attached to the restored image with c atoms in the dictionary; $R_{i,j}$ is the sampling matrix of size m^2-by-N to construct a $\gamma_{i,j}$ vector of size c-by-1 that contain a patch for the part of u. Which contain the encoding coefficients for the patch of u represented in the dictionary; P = $\{1,2,\ldots,n-m+1\}^2$ denotes the index set for different patches of u; $\|.\|_2$ denotes the Euclidean norm of a vector; $\|.\|_0$ denotes the number of non-zero elements; The parameter λ is a positive parameter of data fitting term, and $\mu_{i,j}$ is the positive patch-specific weight. Then perform total variation regularization based on the ideas of sparse representation and energy minimization methods. This work present an efficient algorithm, one dictionary learning step and then solve the TV model with fixed dictionary. The equation used for total variation model is shown below

$$\min_{u \in U \cap BV(\Omega)} TV(u)$$

Where

$$\min_{p \in C_c^1(\Omega R^2)} \{ \int_{\Omega} u \, dtv \, p \, dx : |p(x)| \leq 1 \}$$

$$|p| = \sqrt{p_1^2 + p_2^2} \quad \text{with } p = (p1, p2)$$

$$BV(\Omega) = \{u \in L^1(\Omega) : TV(u) < +\infty\}$$

And ∇, div are the gradient and divergence operator respectively. Here propose a primal-dual algorithm to solve this model effectively. The first order primal dual algorithm to update the restored image.

IV. Observation and Analysis

The qualities of decompressed images are assessed in terms of PSNR and SSIM.

Table 1. Observation and Analysis

Method	Computational Time	PSNR	SSIM
Mean Field Annealing[1]	High	Average	Average
Hybrid Post-processing[2]	High	Average	Average
Total Variation Regularization[3]	High	Average	Average
Classical K-SVD[4]	High	Average	Average
K-SVD+TV[5]	High	High	High

Different techniques which are used to reduce the artifacts in compressed and decompressed domain have been reviewed in this work. From this work it is analyzed that novel strategy learned dictionary with total variation regularization is the efficient method for reducing artifacts is quite computationally demanding.

V. Conclusion

JPEG compression is the popular compression techniques which are used frequently in the real world for compression and decompression purpose. In this technique, the quality of images is reduced compared to original image after decompression. JPEG decompression consists of some visible artifacts such as blocking artifacts, ringing artifacts gibbs artifacts, etc. In this literature, different techniques used to reduce the visible artifacts in compressed and decompressed domains have been reviewed. It has been observed from the literature the novel strategy, learned dictionary with total variations which provide better PSNR and Structural Similarity. But this method is quite computationally demanding.

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References

1. Ozcelik, Taner, J. C. Brailean, and A. K. Katsaggelos. "Image and video compression algorithms based on recovery techniques using mean field annealing." Proceedings of the IEEE 83.2 (1995): 304-316.
2. Shen, Mei-Yin, and C-C. Jay Kuo. "Review of postprocessing techniques for compression artifact removal." Journal of Visual Communication and Image Representation 9.1 (1998): 2-14.
3. Bredies, Kristian, and Martin Holler. "Artifact-free JPEG Decompression with Total Generalized Variation." VISAPP (1). 2012.
4. Aharon, Michal, Michael Elad, and Alfred Bruckstein. "K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation." IEEE Transactions on Signal Processing 54.11 (2006): 4311-4322.
5. Chang, Huibin and Ng, Michael K and Zeng, Tieyong." Reducing Artifact in JPEG Decompression via a Learned Dictionary." IEEE Transactions on Image Processing Image Processing 2014.
6. Matsuoka, Ryuji, Mitsuo Sone, Kiyonari Fukue, Kohei Cho, and Haruhisa Shimoda. "Quantitative analysis of image quality of lossy compression images." entropy 3, no. 4.13 (2004): 4-06.