Interval-valued JPEG decompression for artifact suppression

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***Abstract*— JPEG is the most used image compression algorithm but block wise DCT compression methods produce artifacts due to coefficient quantization. JPEG decompression can be seen as a reconstruction problem constrained by quantization. In this context, we propose to handle this problem by using interval-valued arithmetic. Our method allows to produce interval-valued image that includes the non-compressed original image. The produced convex set allows to apply constrained Total Variation (TV) reconstruction in order to reduce JPEG artifacts (blocking, grainy effects and high frequency noise). Experiments show visual improvement of JPEG decoding assessed by non-reference quality metric. In addition, the stopping *criterion* of the TV algorithm is given by this metric which provides evidence about JPEG decompression improvement.**

***Keywords*— JPEG decompression, interval-valued arithmetic, JPEG artifact removing, image reconstruction, image selection.**

I. Introduction

Digital images are widely used for information exchange, social network or visualization. Therefore, digital image storage and transmission are one of the main challenge in the field of image processing. The most popular image compression standard is JPEG [1]. JPEG efficiency comes from lossy compression and minimum redundancy codes. The IJG (Independent JPEG Group) has standardized the compression and decompression steps. The bitstream produced by the codec is often encapsulated into the JPEG File Interchange Format (JFIF) [2]. JPEG compression consists of four main steps. First, the image color space is transformed from RGB to YCbCr. Then, each channel is divided into non-overlapping $N \times N$ blocks (basically $N = 8$) and each block is transformed using Discrete Cosine Transform (DCT). Afterwards, each block is quantized using a $N \times N$ quantization table (QT). Generally, there are two quantization tables one for the luminance channel and another for the chrominance channels. The quantization process rounds the quotient which induces loss of information. Finally, blocks are compressed using Huffman or arithmetic coding. The DCT decomposes then the signal into $N \times N$ frequencies from the lowest to the highest. Human Visual System (HVS) is sensitive to luminance and blocking effects and is less sensitive to high frequencies which can therefore be more quantized. Main problem in JPEG compression with low quality factor is the degradation of texture, grainy effects and block artifacts [3]. Previous work has focused on methods that remove these artifacts. Some methods focus on removing artifacts on the decompressed RGB image as a post processing such as denoising filter [4]. Reducing artifact may also be done in the frequency domain by modifying boundary DCT coefficients [5], [6]. In [7], a method based on Regression Tree Fields aggregates the prediction of other algorithms to improve their individual contribution. More recently, with the increasing of machine learning, some methods based on learning from image database were proposed *e.g.* via learned dictionary [8] or by deep learning [9]. Such methods rely on the training database and do not guarantee that the final reconstruction belongs to the set of all possible images that could have produced the JPEG compressed image. In this context, intervals of DCT coefficients define a Quantization Constraint Set (QCS), which is the set of the all the possible DCT images in which the image before quantization belongs. This convex set can be used by the projection onto convex sets algorithm [10]. It is efficient for removing blocking artifacts but has low computational performance, due to the processing of both forward and Inverse DCT (IDCT) at each iteration of the algorithm. Therefore, authors have proposed to process the IDCT on the QCS to produce a highly sparse matrix to get a sparse estimate of the Image Quantization Constraint Set (IQCS), the set of all possible images. Then, the selection of the best image is dealt by using a regularization function such as total variation (TV) [11], learned dictionary [8], total generalized variation [12], [13], Markov Random Field using field of expert [14], [15]. Some authors also proposed a Gaussian approximation of the QCS [16] which improves the reconstruction algorithm convergence. Their method requires few iterations but the computation time is increased because they need both forward and inverse DCT for each iteration.

In this paper, we propose an efficient JPEG decompression method for images, that does not require additional information. This method follows standard JPEG decoding steps. Our approach focuses on interval-valued based dequantization of the quantized DCT coefficients of JPEG images. Each DCT coefficient is then represented by an interval which contains the original DCT value forming the QCS. Estimating the best value inside each DCT coefficient interval is not trivial since DCT coefficients are badly correlated. Therefore, we propose an interval-valued IDCT to keep track of the errors across JPEG decompression steps. The resulting interval-valued image is then a convex hull containing all possible images whose compressed image is the current JPEG image. The method requires only one interval-valued IDCT on the convex hull which has the same size of the image, keeping our method fast and low memory consuming. This leads us to an

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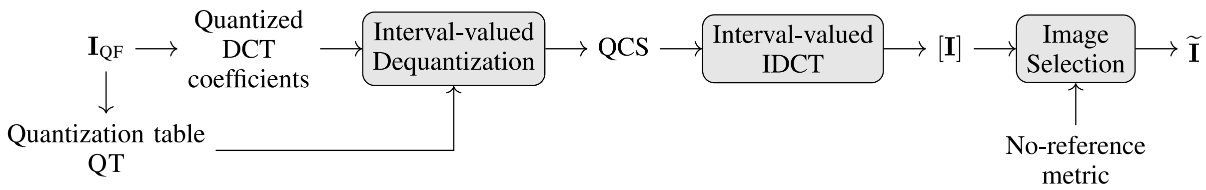


Fig. 1: Framework of the method: an interval-valued dequantization is applied on JPEG compressed image $\mathbf{I}_{\mathrm{QF}}$ producing a QCS. Then, the proposed Interval-valued IDCT transforms it into the spatial domain producing an interval-valued image $[\mathbf{I}] = [\underline{\mathbf{I}}, \overline{\mathbf{I}}]$. Finally, a regularization based on total variation is used to reconstruct the image $\mathbf{I}$.

image selection problem in the spatial domain. This problem is solved by using a TV regularization approach, with a number of iterations defined by a no-reference metric. This method generates a visually nice estimate of the original image.

In Section II, we present the proposed method, by developing the interval-valued dequantization, the interval-valued IDCT and the selection problem. Results are presented in Section III. Finally, Section IV, concludes the paper and provides some hints for future work.

II. The proposed interval-valued JPEG decompression method

In JFIF files, quantization tables are either stored in the header or are easily computable. The method we propose in this paper is outlined in in Fig. 1. It focuses on the image luminance component. The first step consists in associating, to each quantized value in the frequency domain, the interval of all values that could have been its original. The second step consists in using the fact that the IDCT is linear to define an interval-valued IDCT (IIDCT). It produces an interval-valued image $[\mathbf{I}]$, which, by construction, contains all the IQCS. Finally, we use a TV based selection method with no-reference to select the best estimate of the original image.

A. Interval-valued dequantization

JPEG compression scheme is based on splitting the image into M non overlapping $N \times N$ blocks $B_k,\ k \in [0, M-1]$, performing a DCT to each block and then quantizing each coefficient $F_k(u,v)$ of each block B_k. The quantization operation is a pair-wise division of each coefficient $F_k(u,v)$ of the block B_k by the quantization $\mathrm{QT} = \{q(u,v) \mid (u,v) \in [0, N-1]^2\}$. This step is performed in order to encode the quantized DCT coefficients $F'_k(u,v)$ on 8 bits integers. This operation induces the main loss of information in JPEG compression:

$$F'_k(u,v) = round\left(\frac{F_k(u,v)}{q(u,v)}\right), \tag{1}$$

where $round(\cdot)$ represents the nearest half up rounding operator. We denote Q the rounding quantization of a DCT coefficient: $F'(u,v) = Q(F(u,v))$. The JPEG decompression process consists in reversing the JPEG compression steps. Therefore, the dequantization consists of multiplying the quantized DCT coefficients $F'(u,v)$ by their corresponding frequency quantizer $q(u,v)$ to obtain $\hat{F}_k$ an estimate of F_k:

$$\hat{F}_k(u,v) = F'_k(u,v) \times q(u,v). \tag{2}$$

Inverting the DCT to return into the spatial domain is usually performed by applying an IDCT on each block. For a block B_k the IDCT is applied on its dequantized coefficients $\hat{F}_k(u,v)$ which leads to get a sub-image $\hat{\mathbf{I}}_{\mathbf{k}}$ by clipping the obtained values into the $[0, 255]$ integer range. The set of the M sub-images $\hat{\mathbf{I}}_{\mathbf{k}}$ forms the uncompressed image $\hat{\mathbf{I}}$. Let us now define $[F_k(u,v)] = \{F_k(u,v) \mid Q(F_k(u,v)) = F'_k(u,v)\}$. By construction $[F_k(u,v)]$ is convex and its lower bound $\underline{F}_k(u,v)$ and upper bound $\overline{F}_k(u,v)$ can be easily computed by:

$$\underline{F}_k(u,v) = F'_k(u,v) \times q(u,v) - \frac{q(u,v)}{2}, \tag{3}$$

$$\overline{F}_k(u,v) = (F'_k(u,v) + 1) \times q(u,v) - \frac{q(u,v)}{2}. \tag{4}$$

Obviously, $\hat{F}_k(u,v)$ is the central value of $[F_k(u,v)]$. The set of all values $[F_k(u,v)]$ forms the QCS.

B. Interval-valued IDCT

In this section, we use the efficiency of interval-valued arithmetic to propose a fast Interval-valued Inverse DCT (IIDCT). We adapt the IDCT to work with interval-valued DCT coefficients of the QCS, in order to solve the image selection problem in the spatial domain. The goal is to define an IQCS which is a convex set that contains for sure $\{\mathbf{J} \mid \mathrm{DCT}(\mathbf{J}) \in \mathrm{QCS}\}$. Considering a $N \times N$ block B_k of the image $\hat{\mathbf{I}}$, then the standard IDCT inside B_k is defined by:

$$\hat{\mathbf{I}}_{\mathbf{k}}(i,j) = \frac{2}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} c_{u,v,i,j} \hat{F}_k(u,v), \tag{5}$$

$\forall (i,j) \in B_k$ and where:

$$c_{u,v,i,j} = C(u)C(v) \cos\left(\frac{(2i+1)u\pi}{2N}\right) \cos\left(\frac{(2j+1)v\pi}{2N}\right), \tag{6}$$

with $C(\alpha) = \frac{1}{\sqrt{2}}$ if $\alpha = 0$ and 1 otherwise. In this context of interval-valued dequantization, DCT coefficient scalar values are replaced by intervals, therefore the formula is adapted by replacing classic arithmetic operators by their corresponding

Minkowsky operators [17]. The Minkowsky addition is defined by:

$$[x] \oplus [y] = [\underline{x} + \underline{y}, \overline{x} + \overline{y}]. \quad (7)$$

The Minkowsky multiplication by a scalar value $c \in \mathbb{R}$ is defined by:

$$[x] \times c = \begin{cases} [c \times \underline{x}, c \times \overline{x}] & \text{, if } c \geq 0 \\ [c \times \overline{x}, c \times \underline{x}] & \text{, else.} \end{cases} \quad (8)$$

Using these operators, the IIDCT can be defined by:

$$[\mathbf{I_k}(i,j)] = \frac{2}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} [F_k(u,v)] \times c_{u,v,i,j}, \quad (9)$$

where $\sum$ is the Minkowsky sum. Finally, after block junction, an interval-valued image $[\mathbf{I}]$ is obtained:

$$[\mathbf{I}] = \left[\underline{\mathbf{I}}, \overline{\mathbf{I}}\right] = \mathrm{IIDCT}([F]). \quad (10)$$

By construction, the obtained interval-valued image $[\mathbf{I}]$ is an IQCS since it contains for sure all images whose could have produced the JPEG compressed image. One immediate result is that the selection of the median image is very near to a standard JPEG decompression. The proposed approach avoids to deal with the selection problem in the frequency domain or to perform heavily cost multiple IDCT as proposed by [11], [15], [16].

C. Interval-valued image selection

The selection problem in interval-valued images has been addressed in [18] in the context of super-resolution reconstruction. Once the convex set $[\mathbf{I}]$ that contains all the possible JPEG decompressed images is obtained, we propose to select, within this interval-valued image, the most appropriate candidate $\widetilde{\mathbf{I}} \in \mathbb{R}^{w \times h}$ $(w, h \in \mathbb{N})$ according to a chosen regularization term that minimizes the unjustified variations caused by the JPEG compression. Plenty of regularization terms could fit for this purpose. In this paper, we propose to use the widely used TV [19] that already has been proven to be efficient for JPEG artifact suppression [11]. The problem we are trying to solve is a constrained minimization problem, where the function to be minimized is the TV and the constraint is the inclusion of the solution $\widetilde{\mathbf{I}}$ in the interval-valued JPEG decompressed image $[\mathbf{I}]$. This problem can be formalized as:

$$\widetilde{\mathbf{I}} = \min_{\mathbf{J} \in \mathbb{R}^2} TV(\mathbf{J}) + ic_{[\mathbf{I}]}(\mathbf{J}), \quad (11)$$

where $ic_{[\mathbf{I}]}$ is the convex indicator function that ensures that $\mathbf{J}$ is included into the convex hull $[\mathbf{I}]$:

$$ic_{[\mathbf{J}]} : \mathbf{J} \mapsto ic_{[\mathbf{I}]}(\mathbf{J}) = \begin{cases} 0 & \text{if } \mathbf{J} \in [\mathbf{I}] \\ +\infty & \text{if } \mathbf{J} \notin [\mathbf{I}] \end{cases}. \quad (12)$$

To solve Eq. (11), we propose to use the widely used primal-dual algorithm presented by Chambolle and Pock in [20]. In this case, it can be formulated, in its proximal form, by:

$$\begin{cases} v^{i+1} = v^i + w^i - \mathrm{prox}_{TV}(v^i + w^i) \\ \mathbf{I}^{i+1} = \max(\min(\mathbf{I}^i - \frac{1}{2} v^{i+1}, \overline{\mathbf{I}}), \underline{\mathbf{I}}) \\ w^{i+1} = 2.\mathbf{I}^{i+1} - \mathbf{I}^i \end{cases}, \quad (13)$$

with $\mathrm{prox}_{TV}(\mathbf{X}) = \underset{\mathbf{Y}}{\mathrm{argmin}}(TV(\mathbf{Y}) + \frac{1}{2}|\mathbf{X} - \mathbf{Y}|_2^2)$, $|\bullet|_2$ being the L_2 norm, w^0 and $\mathbf{I}^0$ being initialized to $\frac{1}{2}(\underline{\mathbf{I}} + \overline{\mathbf{I}})$, and v^0 to $0^{w \times h}$. The Chambolle Pock algorithm is an iterative algorithm. Even if the reconstruction process is constrained by the convex hull $[\mathbf{I}]$, if Eq. (13) is run until convergence (the convergence is ensured by construction), over-smoothing of textured regions can occur. In order to prevent this drawback, regularization is usually performed by early stopping iterations. In other words, an iteration number is chosen empirically to stop the algorithm before convergence. As this parameter is content dependent and challenging to choose, we propose to automatically select the stopping *criterion* by using a quality score. It is based on non-reference quality metrics, such as BLIINDS-II [21], BRISQUE [22] or NIMA [23]. The proposed method is thus fully parameter-free. Finally, the iteration number is chosen to obtain the regularized image that maximizes the quality score of the whatever chosen quality metric.

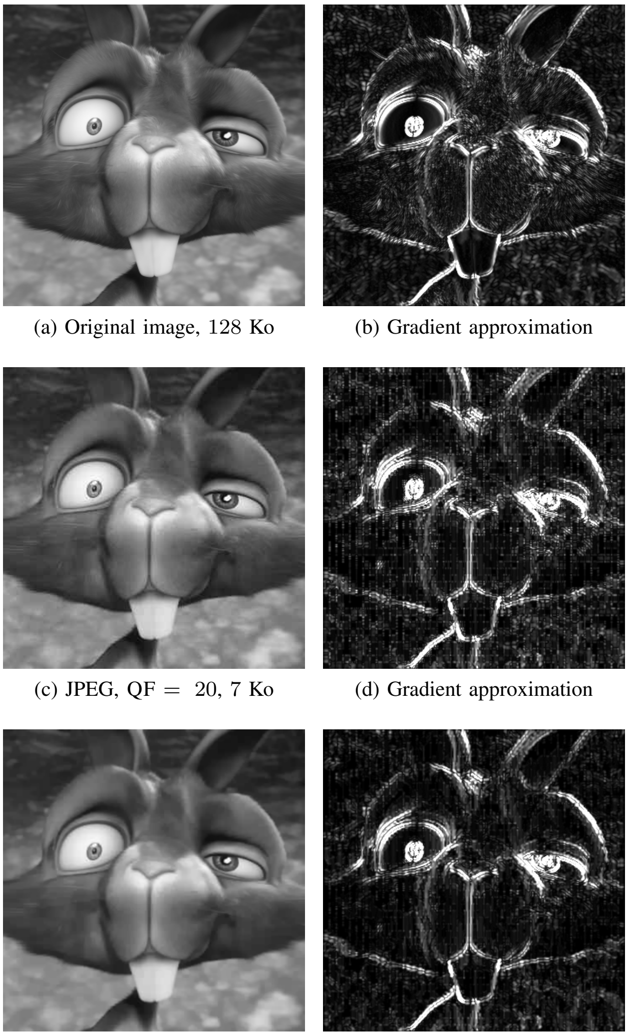
The proposed framework is generic in the sense that it can use any regularization *criteria* and any non-reference quality metrics as stopping *criteria*, depending on the target application. In this paper, L_1 based TV regularization functional has been chosen. The L_1 norm tends to reconstruct smooth uniform areas which leads to remove JPEG compression noise and artifacts [11]. Moreover, due to this smoothing behavior, if a never compressed digital photography is JPEG compressed, the reconstructed image would be similar to the never compressed image without its acquisition noise. Furthermore, since JPEG compression removes high frequencies, the proposed reconstruction method is appropriate since it smooths lost high frequencies areas while preserving edges.

III. Experimental results

For our experimentation, we used standard JPEG quantization tables defined by the IJG (Independent JPEG Group). These quantization tables are generated given a quality factor (noted QF), such as QF $\in [0, 100]$. Decreasing the quality factor increases the compression rate, but generally, alters the visual quality of the image content by producing JPEG artifacts. Also, we proposed to use the NIMA quality assessment method [23] to automatically set the iterations number for regularization, because it seems to be well correlated with the HVS, even for low quality images. Given an image, the metric returns a rate ranged from 1 to 10, with 10 being the highest aesthetic score. Results are assessed in terms of SSIM, PSNR, PSNR-B [24] which take into account the blocking artifacts and the NIMA score which is reference-free and more visually correlated. Experimental results are split into two parts: one focusing on the luminance component, the other on color images.

Luminance case analysis

A first example is presented in Fig. 2. It is a synthetic image from Big Buck Bunny (BBB) [25] (360×360), which has a NIMA score of 5.51, which is JPEG compressed Fig. 2a with a QF $= 30\%$, and decompressed with the standard



(a) Original image, 128 Ko (b) Gradient approximation

(c) JPEG, QF = 20, 7 Ko (d) Gradient approximation

(e) Ours, QF = 20, 7 Ko (f) Gradient approximation

Fig. 2: Result of decompression on an image of the Big Buck Bunny [25] image (360×360) compressed with QF= 30, left column: a) orignal image, c) JPEG decompression and e) the proposed decompression, b), d), f): corresponding gradient Sobel estimate.

method, illustrated in Fig. 2c. Decompression scores using standard JPEG are: PSNR = 37.12 dB, PSNR-B = 37.27 dB, SSIM = 0.93 and NIMA score = 4.77. The proposed approach, presented Fig. 2e, provides better results with PSNR = 37.44 dB, PSNR-B = 38.20 dB, SSIM = 0.94 and NIMA score = 5.00. The proposed decompression is visually more comfortable, and removes JPEG artifacts. This is shown in Fig. 2b, 2d, 2f which represent the approximation of the gradient magnitude given by the combination of horizontal and vertical Sobel filters. Note that JPEG artifacts appear clearly, in Fig. 2d, which corresponds to the standard JPEG. Oppositely, Fig. 2f does not contain gradient on block edges while preserving image content edges as illustrated in Fig. 2b. The high frequency texture of the non compressed image,

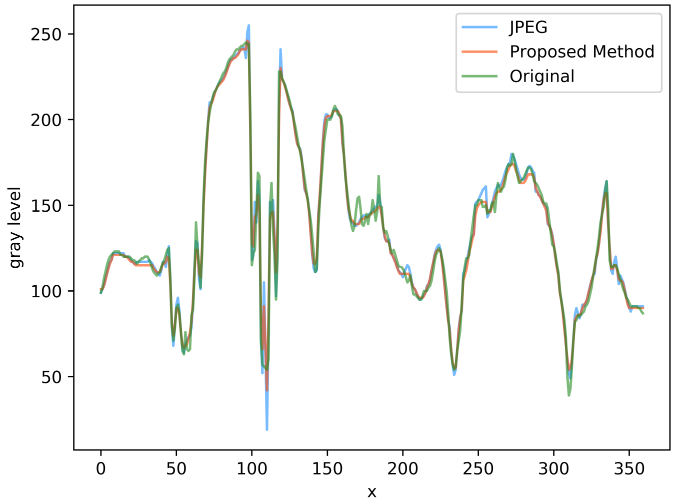


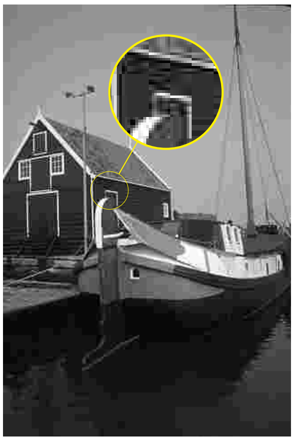
Fig. 3: Horizontal profile curves of the 145^{th} line of the Big Buck Bunny image.

Fig. 2a is lost during JPEG compression, thus the proposed method tends to smooth those areas. The deblocking and edge preserving behavior is illustrated in Fig. 3, which presents the horizontal profiles of the 145^{th} line of the BBB images presented in Fig. 2a, 2b, 2c.

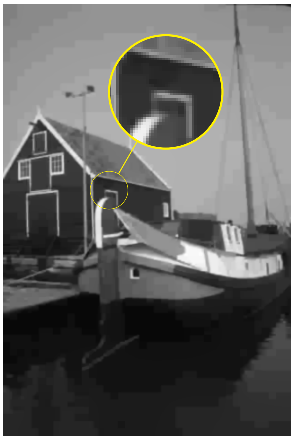
Fig. 4 illustrates the performance in edge preservation of the proposed decompression on a second example. The test image is a natural image of the BSD500 database which has been converted in greyscale. The original image is JPEG compressed with QF = 10%, 20%, 30% and decompressed using standard JPEG and the proposed approach for each quality factor. Globally the image is smoother and most structures are well preserved and enhanced such as boat ropes or the highlighted part. Nevertheless, the reconstruction tends to smooth textured flat areas on which texture is mixed up with artifacts. More experiments have been conducted on the BSDS500 database [26] which is greyscale transformed and compressed with a quality factor QF = 30%. The overall NIMA score over the database is 4.90 with a gain of 1.023 compare to standard a JPEG decompression. Note that using a stopping *criterion* with no reference does not provide the best PSNR or SSIM the method could achieve. Nevertheless, it is just pointing out that these metrics are not enough correlated with the HVS. Moreover, as mentioned in Section II-C, the reconstructed image is also denoised which decreases the score given by the reference metrics.

Color case analysis

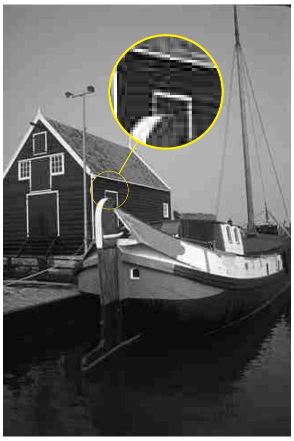
JPEG compression of color images is done separately on each component in the YCbCr color-space. Moreover, standard JPEG implementation sub-samples chrominance channels on which HVS is less sensitive. The standard JPEG subsampling (4:2:2), basically divides by 4 the block size by averaging neighbour pixel values. In this part, we consider this standard JPEG compression which is the most realistic



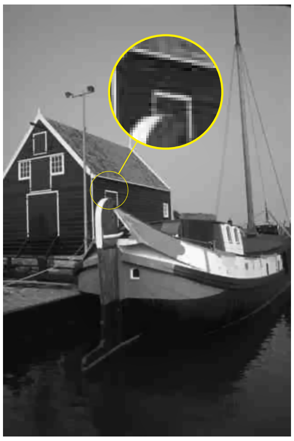
(a) JPEG, QF = 10%



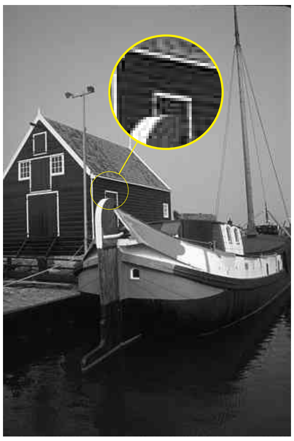
(b) Ours, QF = 10%



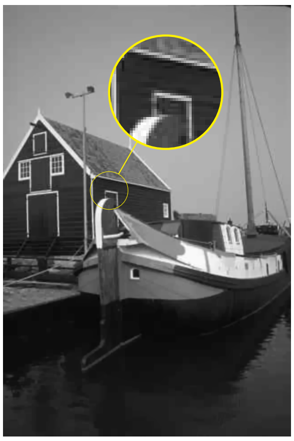
(c) JPEG, QF = 20%



(d) Ours, QF = 20%

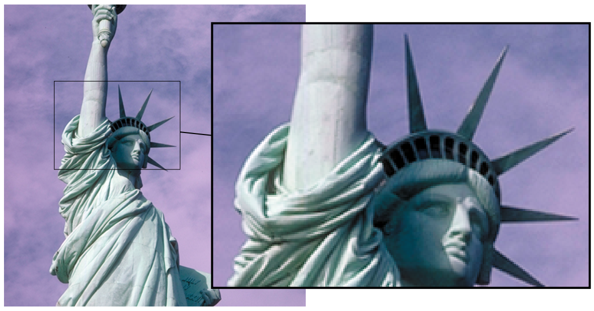


(e) JPEG, QF = 30%

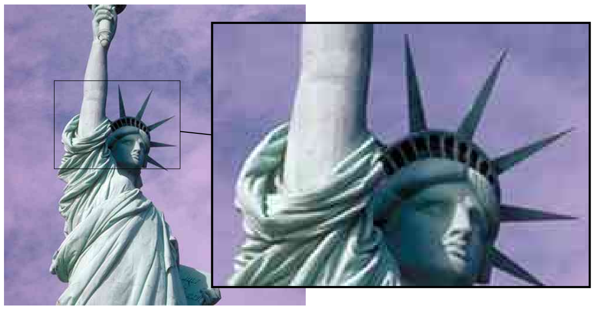


(f) Ours, QF = 30%

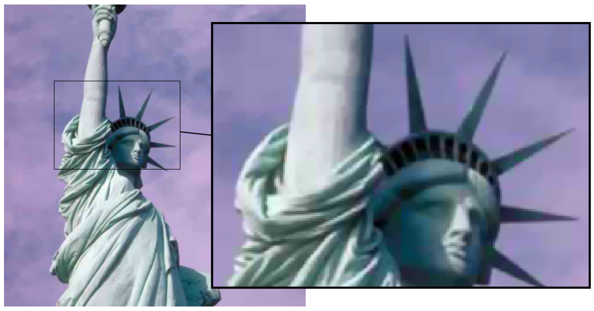
Fig. 4: Result of decompression on an image of the BSD500 database [26] JPEG compressed with QF = 10%, 20%, 30%, left column: standard decompression, right column: decompression with the proposed method.



(a) Original image, 374 Ko



(b) JPEG QF = 30%, 13.9 Ko



(c) Ours QF = 30%, 13.9 Ko

Fig. 5: Result of decompression on the Statue of Liberty image of the CSIQ database [27], compressed with QF = 30%.

scenario. The proposed method can be applied trivially on each channel, if chrominance channels were not sub-sampled. In the case of standard JPEG color images, the luminance channel can be reconstructed independently and space color transformation from YCbCr to RGB can be done without using intervalist reconstruction on chrominance channels. This is illustrated in Fig. 5a, the Statue of Liberty image of the CSIQ database [27], which has a NIMA score = 5.50. The image is JPEG compressed with a QF = 30%, and decompressed with standard method Fig. 5b with PSNR = 33.45 dB, SSIM = 0.92 and NIMA score = 5.09. The proposed approach, presented in Fig. 5c, provides better visual results, even if metrics are similar: PSNR = 32.45 dB, SSIM = 0.92 and NIMA score = 5.17. It can be seen that the proposed method performs well for edge preservation and for smoothing uniform areas. Nevertheless, JPEG artifacts are still visible in the color. This is due to the fact that chrominance channels are more quantized and thus often lead to constant value in a block. Therefore, some blocks appear reddish compared to their neighbors in the sky.

The proposed method can be extended to keep interval valued image through the space color transformation and then reconstruct. Nevertheless, chrominance channels being sub-sampled and more quantized, the produced intervals are larger and their larger errors are propagated during an interval-valued color conversion. The simplest solution is to treat each channel independently before color conversion but the chrominance values are not enough constrained to move away from the center of the intervals.

IV. Conclusion

In this paper, we proposed a new approach to solve JPEG artifact compression problem. The interval-valued solution is useful for limiting the number of transformations *i.e.* it needs only one IIDCT by block. In our knowledge the proposed interval-valued decompression is a new approach. The proposed image selection framework is generic and will be thoroughly analyzed in future work. Results are convincing on gray level images and assessed by recent perceptual metric NIMA. This metric is used as part of the decompression framework and could be replaced by a more effective or specific one. For example, we are planning to train a convolutional neural network (CNN) focusing only on JPEG compressed images and their perceptual estimation by users. In future work, we aim to extend this work more carefully on color images which is non trivial due to the non linear color conversion and JPEG sub-sampling. Therefore, we are investigating for a new method using Interval Based Algebraic Reconstruction Technique [28] which could be efficient to reduce interval range.

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