Image Restoration via Successive Compression

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Abstract—**In this paper we propose a method for solving various imaging inverse problems via complexity regularization that leverages existing image compression techniques. Lossy compression has already been proposed in the past for Gaussian denoising – the simplest inverse problem. However, extending this approach to more complicated inverse problems (e.g., deblurring, inpainting, etc.) seemed to result in intractable optimization tasks. In this work we address this difficulty by decomposing the complicated optimization problem via the Half Quadratic Splitting approach, resulting in a sequential solution of a simpler ℓ_2-regularized inverse problem followed by a rate-distortion optimization, replaced by an efficient compression technique. In addition, we suggest an improved complexity regularizer that quantifies the average block-complexity in the restored signal, which in turn, extends our algorithm to rely on averaging multiple decompressed images obtained from compression of shifted images. Many compression techniques rely on sparsity-seeking procedures and, therefore, sparsity is indirectly included in the regularization of the proposed restoration. We demonstrate the proposed scheme for inpainting of corrupted images, using leading image compression techniques such as JPEG2000 and HEVC.**

I. Introduction

Previous work has considered complexity, measured as the compression bit-cost of candidate solutions, as regularization for image restoration. Several studies (e.g., [1], [2]) suggested complexity-regularized solutions to the Gaussian denoising task, which is the simplest inverse problem, by applying lossy compression on the noisy signal. The extension of the complexity-regularized approach to more complicated inverse problems (e.g., deblurring, inpainting, super-resolution, etc.) was studied in [3], where a thorough theoretical treatment of the problem was provided. However, the practical employment of the approach reached a dead-end in the form of highly intractable optimization tasks, that rarely reduce to reasonable structures. For example, this approach was demonstrated in [3] only for Poisson denoising and with a particularly designed compression architecture.

In this paper, we propose a methodology that enables practical solution of various complexity-regularized inverse problems, removing the limitations on the image deterioration model and the utilized compression method, hence, establishing a generic complexity-regularized approach for image restoration. We suggest to decouple the two intricate parts of the optimization problem via the useful Half Quadratic Splitting approach. Our approach results in an iterative solution involving simpler ℓ_2-regularized inverse problems followed by standard rate-distortion optimizations that can be replaced by any existing compression technique. The proposed approach can be viewed as the compression counterpart of the recent Plug-and-Play Priors framework [4], where restoration problems were solved by an iterative process that relies on an arbitrary Gaussian denoiser, allowing the solution of complicated problems (e.g., see [5]).

As many compression methods operate on non-overlapping blocks in the image, the corresponding complexity measure is shift-sensitive. In order to alleviate this shortcoming, we further extend the complexity regularization to measure the average complexity of all the overlapping blocks in the recovered image. This can be interpreted as a variant of the Expected Patch Log-Likelihood (EPLL) concept [6]. In our case, this approach enhances the proposed procedure, leading to an average of multiple decompressed images following compression of shifted images. Interestingly, this procedure recalls the cycle-spinning approach [7], originally proposed for wavelet-based denoising. Moreover, whereas the compression artifact-reduction techniques in [8], [9] suggest to enhance decompressed images by repeated compressions of their shifted versions that are averaged, here we generalize this approach to address various image restoration tasks.

II. Overview of The Proposed Method

A signal $\mathbf{x} \in \mathbb{R}^N$ is corrupted via $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$, where $\mathbf{H}$ is a matrix representing a deteriorating operation (such as blur, pixel erasure, decimation, etc.) and $\mathbf{n}$ is a vector of white Gaussian noise. The considered task is to restore $\mathbf{x}$ from its corrupted version $\mathbf{y}$.

We suggest to regularize the restoration by the average complexity of all the overlapping blocks in the image, namely,

$$\hat{\mathbf{x}} = \underset{\mathbf{x}}{\text{argmin}} \left\| \mathbf{H}\mathbf{x} - \mathbf{y} \right\|_2^2 + \mu \sum_{i \in \mathcal{B}^*} \bar{r}(\mathbf{P}_i \mathbf{x}), \tag{1}$$

where μ is a parameter weighting the regularization effect, $\mathcal{B}^*$ is the set containing the indices of all the overlapping blocks in the image, and $\mathbf{P}_i$ is a matrix that extracts the i^{th} block from a full signal. In addition, $\bar{r}(\cdot)$ is a block-level rate function associated with a block-based compression technique that relies on a codebook, $\mathcal{C}$, containing a finite set of block reproduction options, each coupled with a binary codeword for its compressed-domain representation. The assumed compression architecture allocates shorter codewords for more likely patterns, and the length of the binary codeword of $\mathbf{z} \in \mathcal{C}$ is evaluated by $\bar{r}(\mathbf{z})$ (where $\bar{r}(\mathbf{z}) = \infty$ for $\mathbf{z} \notin \mathcal{C}$).

Using the Half Quadratic Splitting approach the optimization (1) is translated into the following iterative solution (t^{th} iteration):

$$\hat{\mathbf{x}}^{(t)} = \underset{\mathbf{x}}{\text{argmin}} \left\| \mathbf{H}\mathbf{x} - \mathbf{y} \right\|_2^2 + \frac{\beta^{(t)}}{2} \sum_{i \in \mathcal{B}^*} \left\| \mathbf{P}_i \mathbf{x} - \hat{\mathbf{z}}_i^{(t-1)} \right\|_2^2 \tag{2}$$

$$\hat{\mathbf{z}}_i^{(t)} = \underset{\mathbf{z}_i}{\text{argmin}} \frac{\beta^{(t)}}{2} \left\| \mathbf{P}_i \hat{\mathbf{x}}^{(t)} - \mathbf{z}_i \right\|_2^2 + \mu \bar{r}(\mathbf{z}_i), \; i \in \mathcal{B}^* \tag{3}$$

$$\text{Set } \beta^{(t+1)} \text{ as an increment of } \beta^{(t)}. \tag{4}$$

Here β is an auxiliary parameter introduced by the Half Quadratic Splitting. The step in Eq. (3) consists of block-level rate-distortion optimizations for all the overlapping blocks in the image. We can identify this stage as multiple applications of a full image compression-decompression procedure, each operates on a different set of non-overlapping blocks that forms a corresponding shifted version of the image. We further suggest to replace these rate-distortion optimizations with application of an independent compression technique. Additional details are provided in [10].

We demonstrate our approach for image inpainting, considering the noisy (Table I and Fig. 1) and the noiseless (Fig. 2) corruption models. The proposed technique is evaluated with the JPEG2000 and the HEVC still-image compression methods (see details in [10]), showing impressive restoration results.

(a) Corrupted (b) Exemplar-based [11] (21.60dB) (c) Deterministic-Annealing [12] (26.81dB) (d) Proposed JPEG2000 (25.67dB) (e) Proposed HEVC (25.60dB)

Fig. 2. Restoration of Lena (512×512) from noiseless deterioration of missing square blocks (each of 16×16 pixels). The PSNR values in this experiment are only of the missing regions.

(a) Corrupted (8.87dB) (b) Reconstruction (28.97dB)

Fig. 1. Restoration of Barbara (512×512) from deterioration of 50% missing pixels and noise of $\sigma_n = 5$. The restoration utilized JPEG2000 compression and performed 45 iterations.

TABLE I
NOISY INPAINTING: PSNR RESULTS

Image 512x512	**Missing Pixels**	$\sigma_n = 5$		$\sigma_n = 15$	
		Deteriorated	Recovered	Deteriorated	Recovered
Lena	75%	6.92	31.16	6.86	28.27
	50%	8.67	34.47	8.57	29.12
	25%	11.66	36.54	11.46	29.21
Barbara	75%	7.13	25.29	7.06	24.36
	50%	8.87	28.97	8.77	26.70
	25%	11.87	32.71	11.67	28.26

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REFERENCES

[1] B. K. Natarajan, "Filtering random noise from deterministic signals via data compression," *IEEE Trans. Signal Process.*, vol. 43, no. 11, pp. 2595–2605, 1995.
[2] J. Liu and P. Moulin, "Complexity-regularized image denoising," *IEEE Trans. Image Process.*, vol. 10, no. 6, pp. 841–851, 2001.
[3] P. Moulin and J. Liu, "Statistical imaging and complexity regularization," *IEEE Trans. Inf. Theory*, vol. 46, no. 5, pp. 1762–1777, 2000.
[4] S. V. Venkatakrishnan, C. A. Bouman, and B. Wohlberg, "Plug-and-play priors for model based reconstruction," in *IEEE GlobalSIP*, 2013.
[5] Y. Dar, A. M. Bruckstein, M. Elad, and R. Giryes, "Postprocessing of compressed images via sequential denoising," *IEEE Trans. Image Process.*, vol. 25, no. 7, pp. 3044–3058, 2016.
[6] D. Zoran and Y. Weiss, "From learning models of natural image patches to whole image restoration," in *IEEE ICCV*, 2011.
[7] R. R. Coifman and D. L. Donoho, "Translation-invariant de-noising," in *Wavelets and Statistics*. Springer, 1995, pp. 125–150.
[8] A. Nosratinia, "Enhancement of JPEG-compressed images by re-application of JPEG," *J. VLSI Signal Process. Syst. for Signal, Image and Video Technol.*, vol. 27, no. 1-2, pp. 69–79, 2001.
[9] ——, "Postprocessing of JPEG-2000 images to remove compression artifacts," *IEEE Signal Process. Lett.*, vol. 10, no. 10, 2003.
[10] Y. Dar, A. M. Bruckstein, and M. Elad, "Image restoration via successive compression," in *Picture Coding Symposium*, 2016.
[11] A. Criminisi, P. Pérez, and K. Toyama, "Region filling and object removal by exemplar-based image inpainting," *IEEE Trans. Image Process.*, vol. 13, no. 9, pp. 1200–1212, 2004.
[12] X. Li, "Image recovery via hybrid sparse representations: A deterministic annealing approach," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 5, pp. 953–962, 2011.