Dictionary Learning-based Image Compression

Hao Wang[1], Yong Xia[1*], Zhiyong Wang[2]

[1]Northwestern Polytechnical University, [2]University of Sydney

Introduction

➢ **Motivation of the paper:** amongst nature images, there are many similar structures and ranges. If all these similar structures were organized into a particular form of dictionary, an image could be represented by a combination of several dictionary atoms, in which only indices of the dictionary atoms and the corresponding weights need to be recorded.

➢ **Contributions of the paper:**

I. The Entropy based Orthogonal Matching Pursuit (EOMP) algorithm is proposed. An entropy regularization term is utilized in EOMP to restrict atom selection, and hence reduces the coding cost.

II. The Quantization KSVD (QKSVD) dictionary learning algorithm is introduced, where an adaptive quantization method is incorporated into the dictionary learning procedure to minimize the reconstruction error and quantization error simultaneously.

Method

The framework of the image compression algorithm is shown in Fig. 1.

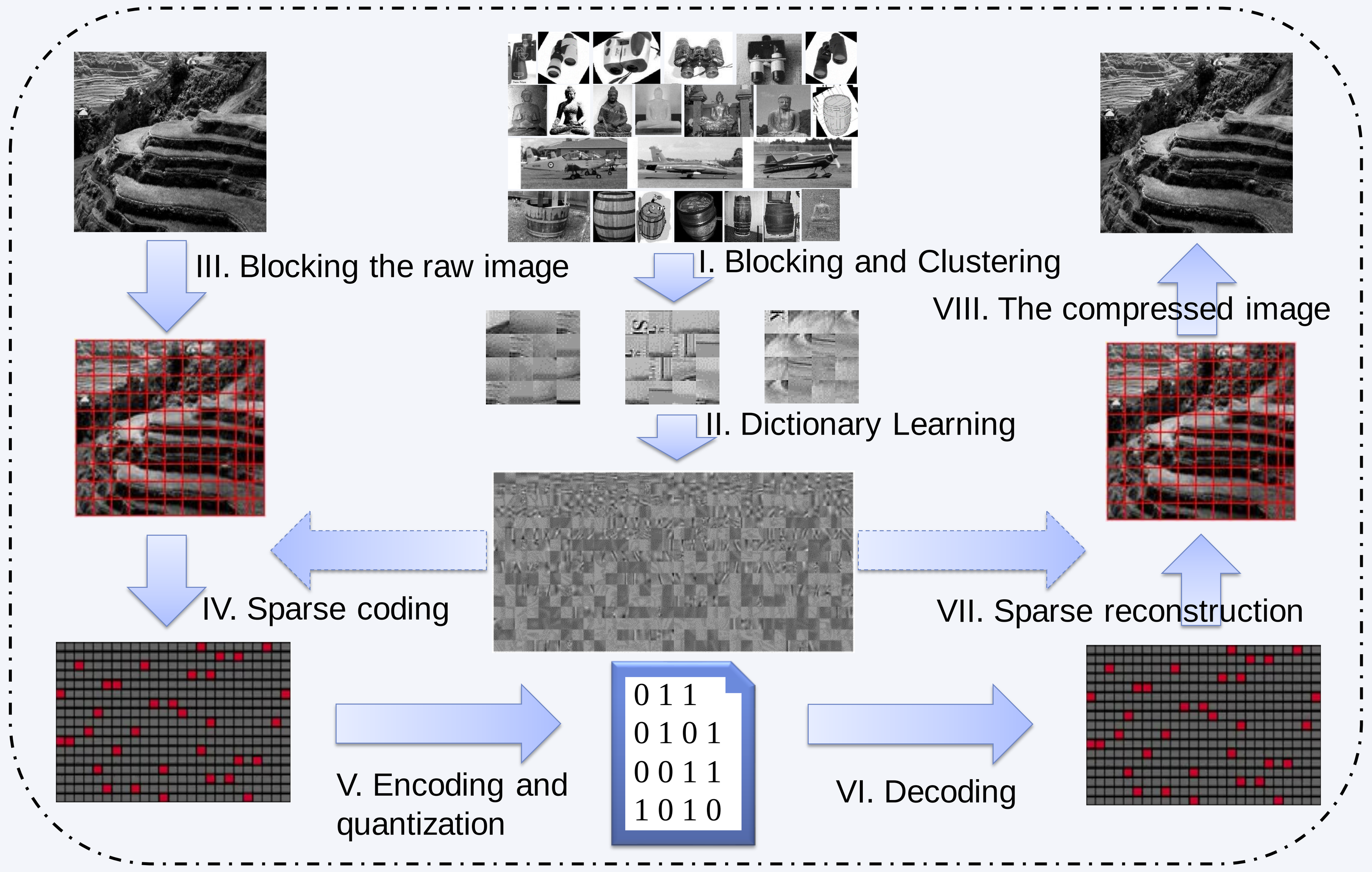

Fig. 1. The framework of the compression algorithm

In dictionary learning, the proposed EOMP and QKSVD algorithms are applied to learn the corresponding dictionaries and quantization tables to those clusters by optimizing Eq. 1 and Eq. 2 iteratively, and all learned dictionaries and quantization tables are concatenated into a universal dictionary and a merged quantization table respectively.

$$\hat{A} = \arg\min_{A}\{\|S - DA\|_F^2 - \eta p^T \log p\} \quad s.t. \left\|a_{\cdot j}\right\|_0 \le k_{max} \tag{1}$$

$$\hat{D} = \arg\min_{D}\|S - D \cdot Q(A)\|_F^2 \quad s.t. \left\|a_{\cdot j}\right\|_0 \le k_{max} \tag{2}$$

Here, S is the ensemble of mean-subtracted patches, D is the dictionary, A is the ensemble of sparse reconstruction coefficients, $a_{\cdot j}$ is the j^{th} column in A, k_{max} is the sparsity constraint, p is a probability vector with each element representing the probability of the selecting atom, $Q(\cdot)$ is a non-uniform quantization function.

To quantize larger coefficients with a larger step length and smaller ones with smaller step length, all sparse coefficients are sorted and divided into different groups by minimizing the following sum of square error:

$$\{\hat{L}_1, \hat{L}_2, \cdots, \hat{L}_k\} = \arg\min_{\{L_1, L_2, \dots, L_k\}} \sum_{i=1}^{k} \sum_{j}^{|L_i|} \left(a_{i_j} - \bar{L}_i\right)^2 \tag{3}$$

Here, L_i is the i^{th} group, $\bar{L}_i$ is the mean of L_i, a_{i_j} is the j^{th} element of L_i. step length is different among L_i's, but the same inside L_i.

Results

The proposed algorithm was compared against JPEG, JPEG-2000 and the KSVD algorithms on 10 benchmark images shown in Fig. 2. The quality of compressed images was measured by the peak signal-to-noise ratio (PSNR).

Fig. 2. from left to right and top to bottom, it's the *baboon*, *boat*, *cell*, *couple*, *elaine*, *lena*, *man*, *peppers*, *photography*, and *satellite* respectively.

The PSNRs of the ten test images compressed at different bit rates were given in Table 1. It shows that JPEG-2000 and KSVD have a similar performance, and the proposed algorithm achieves the highest PSNR on six out of ten test images when the bit rate is low.

Table 1. The PSNRs of the ten images compressed by JPEG (top left), JPEG-2000 (top right), KSVD(bottom left) and the proposed algorithm (bottom right) at different bit rates.

Baboon	0.18bpp		0.26bpp		0.34bpp	
	20.18	22.78	21.84	23.76	23.02	24.80
	23.98	26.07	24.99	26.46	25.75	26.95
Boat	0.16bpp		0.23bpp		0.28bpp	
	25.12	29.32	27.67	30.95	29.25	32.08
	29.65	29.90	30.23	30.69	31.19	31.47
Cell	0.16bpp		0.21bpp		0.25bpp	
	27.31	35.79	31.13	37.77	33.07	38.75
	29.66	30.15	30.28	30.89	30.51	31.33
Couple	0.17bpp		0.23bpp		0.29bpp	
	25.44	30.27	27.96	31.71	29.86	32.85
	30.78	31.09	31.56	32.24	32.51	33.11
Elaine	0.17bpp		0.23bpp		0.28bpp	
	28.73	33.96	31.46	34.85	32.89	35.47
	32.85	32.99	33.66	33.80	34.19	34.20
Lena	0.16bpp		0.21bpp		0.25bpp	
	25.89	31.46	28.60	32.68	30.21	33.84
	31.73	32.04	32.63	32.75	32.43	32.59
Man	0.18bpp		0.25bpp		0.32bpp	
	23.88	26.73	25.96	28.06	27.29	29.14
	28.55	29.58	29.99	30.34	30.64	30.86
Peppers	0.16bpp		0.21bpp		0.25bpp	
	25.97	32.71	29.64	34.19	31.12	35.11
	31.79	31.93	31.96	32.81	32.19	32.88
Photograph y	0.11bpp		0.15bpp		0.18bpp	
	24.73	31.02	26.59	32.04	29.21	33.92
	31.16	31.16	31.98	32.10	32.63	32.65
Satellite	0.18bpp		0.25bpp		0.33bpp	
	23.67	27.09	26.11	28.12	27.13	29.01
	23.34	23.56	24.07	24.44	25.45	25.55

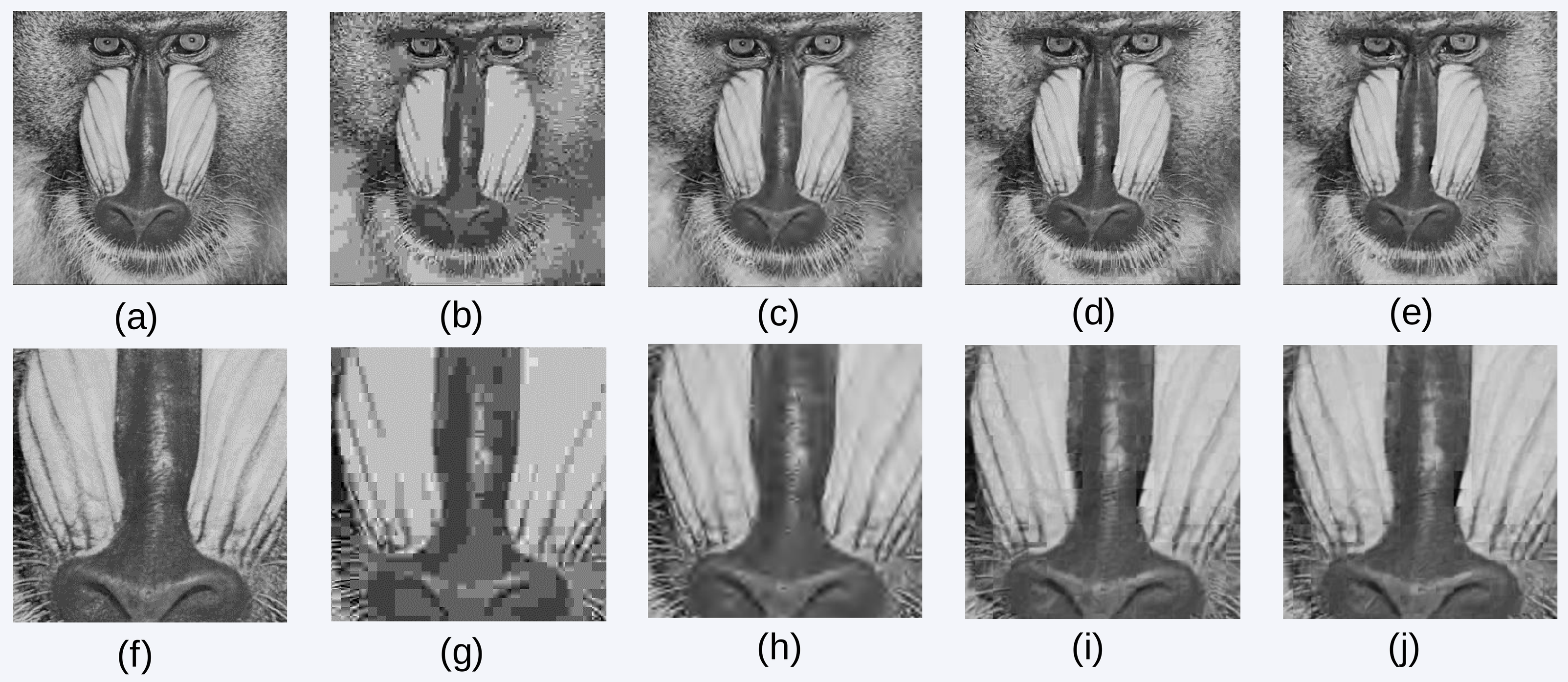

Fig. 3. (a) Original test image Baboon and its compressed versions generated by (b) JPEG, (c) JPEG-2000, (d) KSVD and (e) the proposed algorithm.

Conclusion

In this paper, we present a novel dictionary learning-based image compression approach, which employs the newly designed EOMP and QKSVD algorithms. Our pilot results suggest that the proposed approach is able to achieve better image compression performance than the benchmark JPEG, JPEG-2000 and KSVD algorithms.

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