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Image Compression Via Sparse Reconstruction

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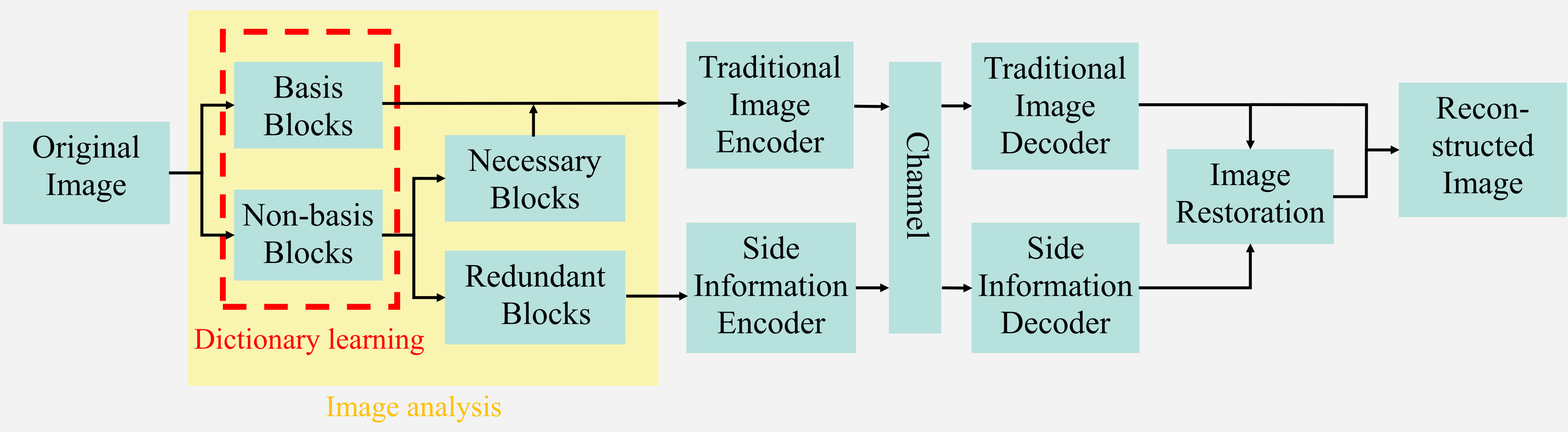
Introduction

In this paper, we propose a novel image compression approach based on the ***removal*** and ***reconstruction*** of the visual redundancy blocks at the encoder and decoder respectively.

- At the encoder, we use ***dictionary learning*** in sparse model to optimally select and remove several redundant blocks.
- At the decoder, we design an ***alternate iterative image restoration*** method to reconstruct the removed blocks.

The experimental results demonstrate that our approach achieves up to 13.67% bit rate reduction with a comparable visual quality compared to High Efficiency Video Coding (HEVC).

Flowchart of the proposed scheme



- The basis blocks are a sub-set of image blocks that are capable of reconstructing the image with minimum reconstruction error.
- Some non-basis blocks will be preserved to further enhance the visual quality if the reconstruction errors are relatively large.

Encoder: Redundant Blocks Selection

Step 1: Learning Basis Blocks

Goal: Find a set of basis patches, which are able to reconstruct the whole image with minimum reconstruction error.

$$\min_{D,A} \sum_{i=1}^{N_p} \| R_i y - D\alpha_i \|_2^2$$
$$s.t. \quad \forall i, \|\alpha_i\|_0 \le L$$
$$d_k \in \psi$$

Symbols:

- y is the column stacked version of original image
- K is a tunable parameter which controls the number of the basis patches
- R_i is a matrix to extract the *ith* patch of the image
- $A = [\alpha_1, \alpha_2, ..., \alpha_{N_p}]$ is the sparse coefficient matrix
- $D = [d_1, d_2, ..., d_K]$ is the dictionary with K bases
- $\psi = \{\psi_1, \psi_2, ..., \psi_{N_p}\}$ is the set of all the patches in image

We relax the cost function into two sub-problems:

- Obtain the dictionary bases which can be any real vectors by OMP
- Find the most similar patch for each basis by minimizing the L2 norm

Step2: Identifying redundant blocks

Goal: Select some redundant blocks to remove from the non-basis blocks.

- Removal Priority of a block:

$$\rho(i) = (c + \sum_{B_j \in N(B_i)} w_j) \cdot \exp\left(-\frac{\sum_{k \in B_i} (y_k - x_k)^2}{2\sigma^2}\right)$$

Confidence term ← → Data term

- Confidence term reflects the state of the four neighbor blocks whether they are removed or preserved.
- Data term measures the similarity between the reconstructed block and the original block.

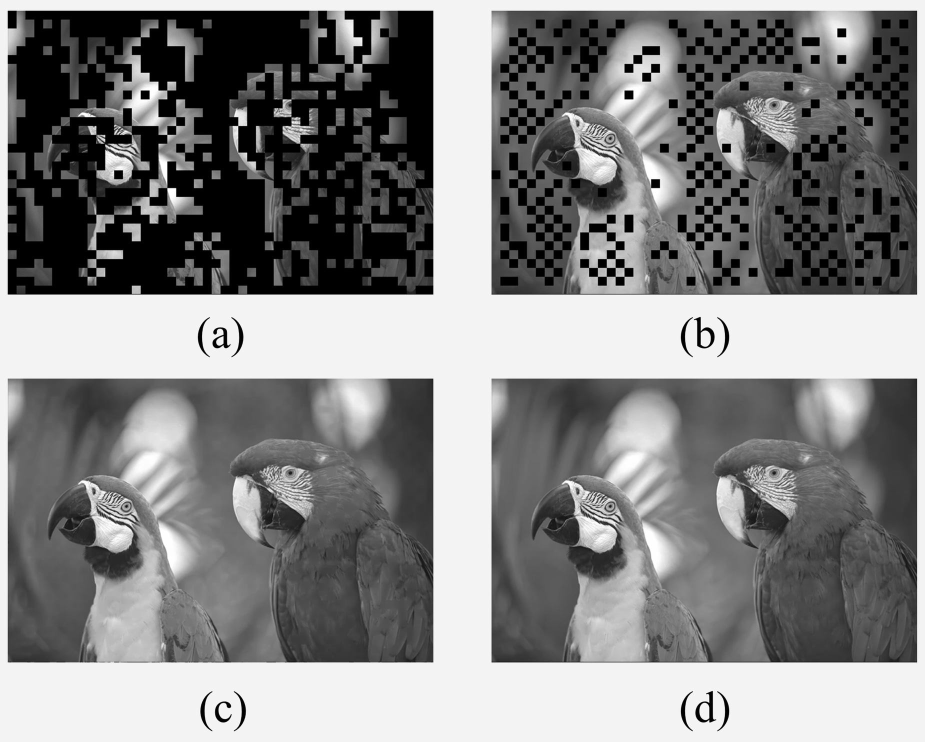


Figure 1: An example of the proposed scheme.

(a)The image with basis blocks
(b)The image with basis blocks and necessary blocks
(c)The reconstructed image obtained by proposed scheme
(d)The reconstructed image obtained by HEVC

Decoder: Image Restoration

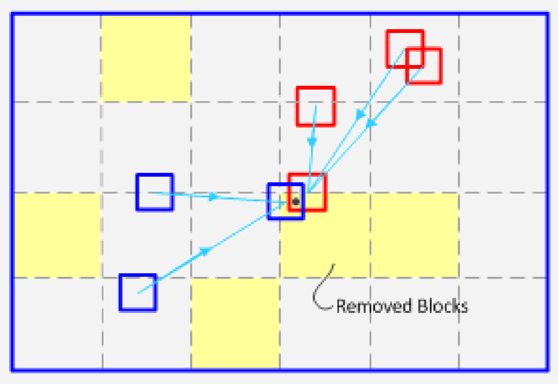
- Given $\hat{y}$, find the optimal A to minimize the reconstruction error
- Given A, update the pixel values in the missing region of $\hat{y}$
- The iteration is repeated until $\| \hat{y}^{(t+1)} - \hat{y}^{(t)} \| < \varepsilon$

Step 1:

$$\min_{A^{(t+1)}} \sum_i \| R_i \hat{y}^{(t)} - \tilde{D}\alpha_i^{(t+1)} \|_2^2$$
$$s.t. \quad \forall i, \|\alpha_i^{(t+1)}\|_0 \le L$$

Step 2:

$$\hat{y}_j^{(t+1)} = \frac{\sum_{j \in \Psi_i} s_i^{(t+1)} e_{ij}^T \tilde{D}\alpha_i^{(t+1)}}{\sum_{j \in \Psi_i} s_i^{(t+1)}}$$



Experimental Results

Table 1. Bit-saving compared to HEVC intra coding (QP=24)

Test Image	*Image Size*	*Remove Rate*	*Bit-rate(bpp) Proposed*	*Bit-rate(bpp) HEVC*	*Bit-rate saving*
BasketballDrill	480 × 832	25.10%	0.7231	0.798	**9.38%**
Kodim23	512 × 768	26.70%	0.4625	0.5207	**11.17%**
Peppers	512 × 512	23.10%	0.9749	1.1294	**13.67%**

Subjective Comparison:

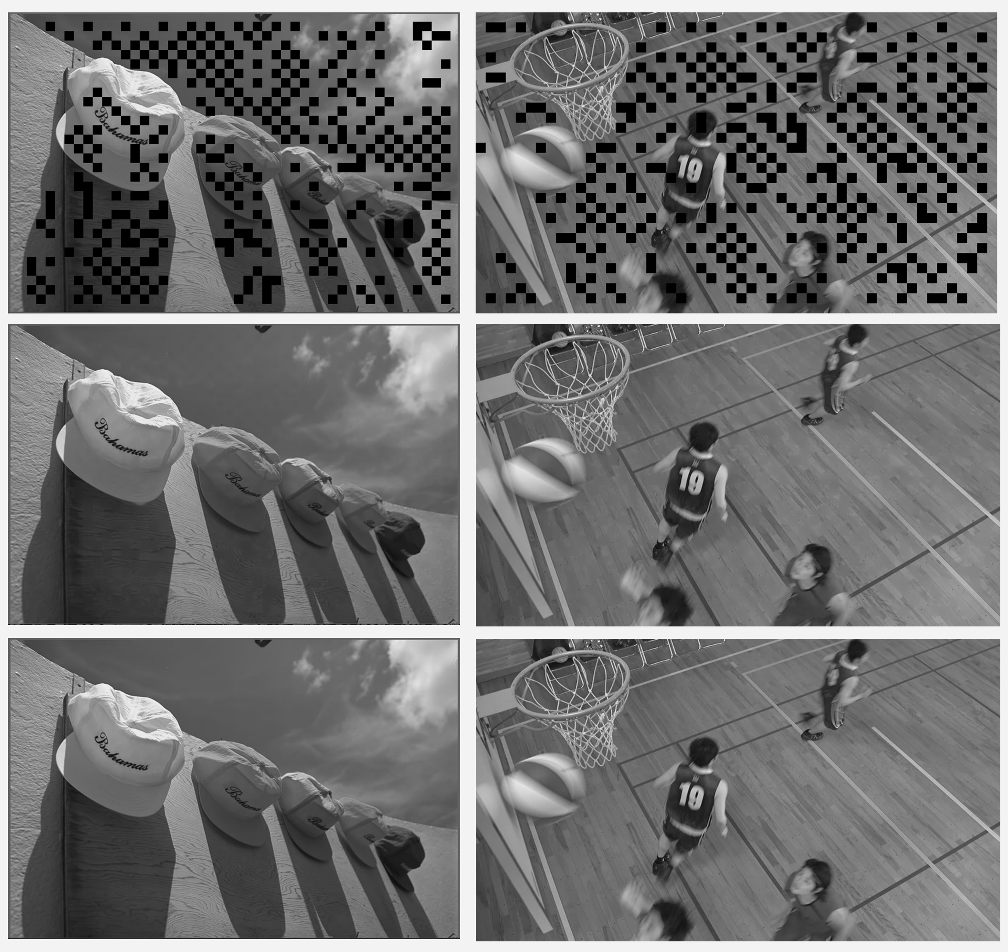


Figure 2: Top: Incomplete image. Middle: Reconstructed image by proposed method. Bottom: reconstructed Image by HEVC.

Objective Comparison:

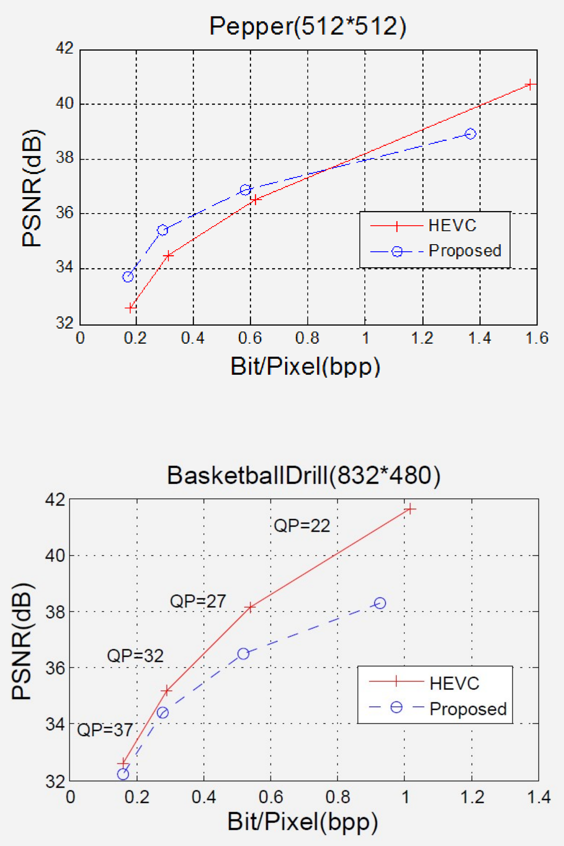


Figure 3: Objective comparison between proposed method and HEVC.