AdderIC: Towards Low Computation Cost Image Compression

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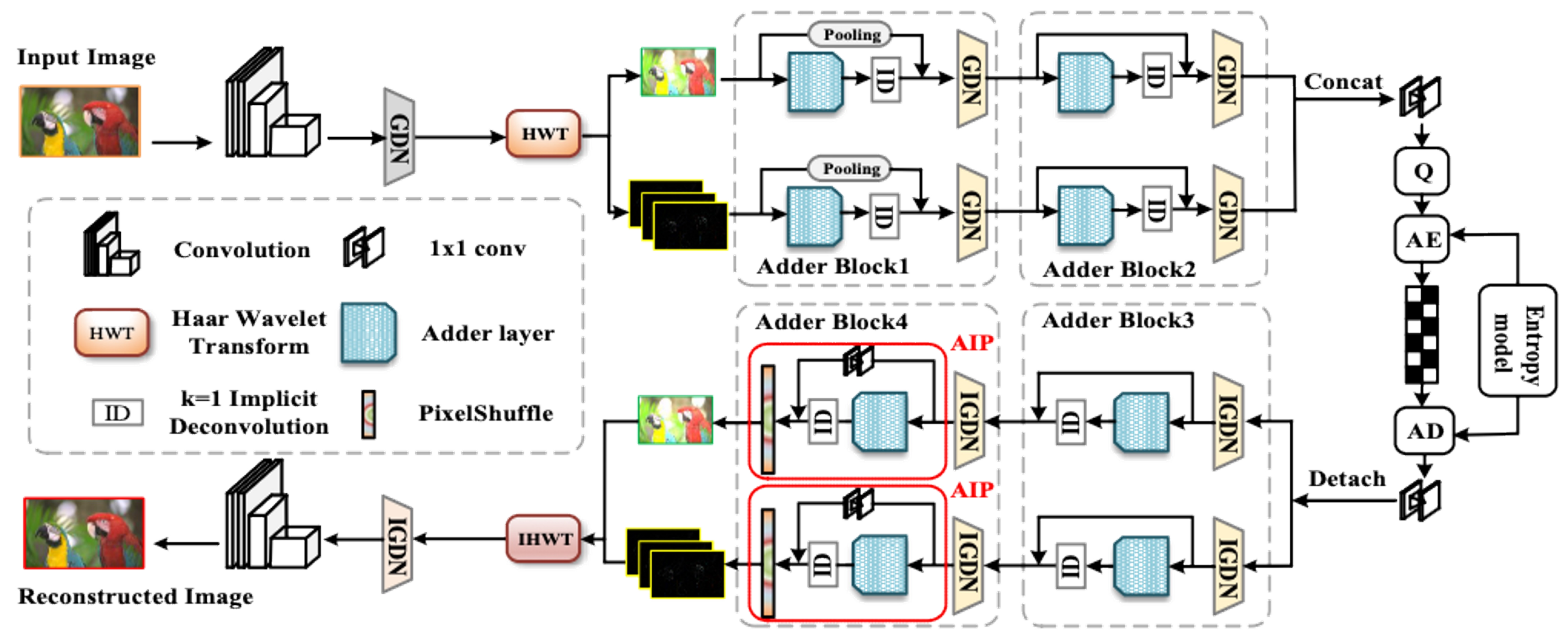
Introduction

Recently, learned image compression methods have shown their outstanding rate-distortion performance when compared to traditional frameworks. Although numerous progress has been made in learned image compression, the computation cost is still at a high level. To address this problem, we propose AdderIC, which utilizes adder neural networks (AdderNet) to construct an image compression framework. According to the characteristics of image compression, we introduce several strategies to improve the performance of AdderNet in this field.

Methods

- First, We introduce Haar Wavelet Transform (HWT) to enable AdderIC to learn high-frequency information efficiently;
- In addition, implicit deconvolution (ID) with a kernel size of 1 is adopted to reduce spatial redundancies;
- Furthermore, we develop a novel Adder-ID-PixelShuffle (AIP) upsampling structure to remove checkerboard artifacts in the decoder.

Architecture



Experiment

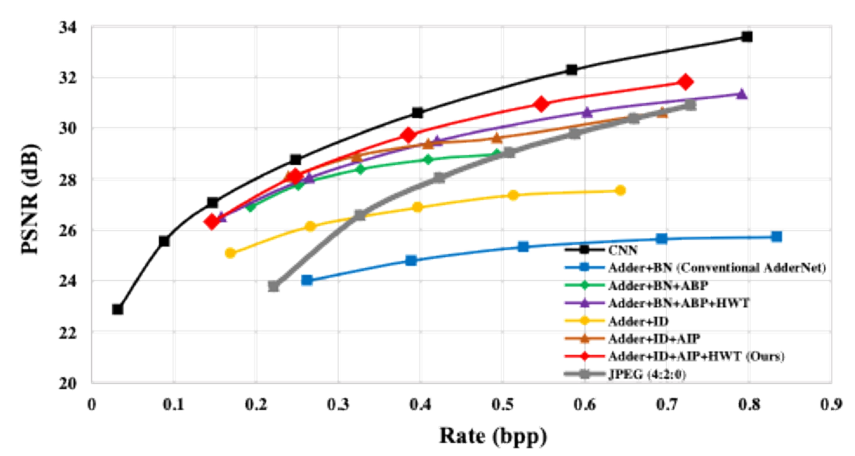


Fig. 4. PSNR on Kodak Dataset

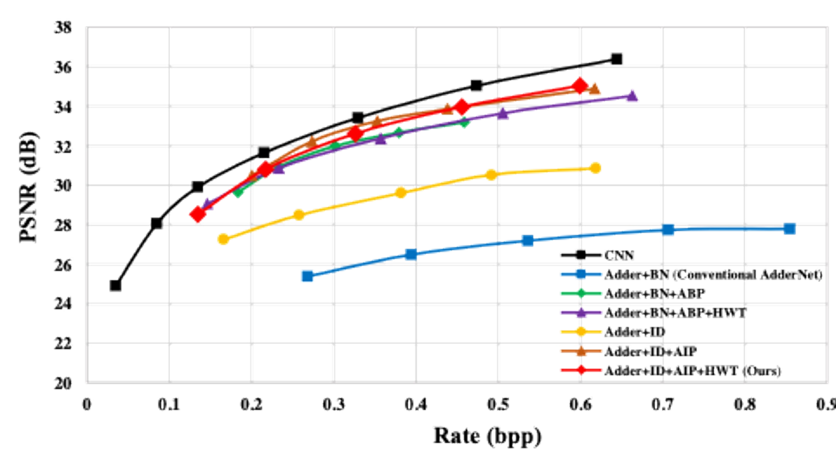
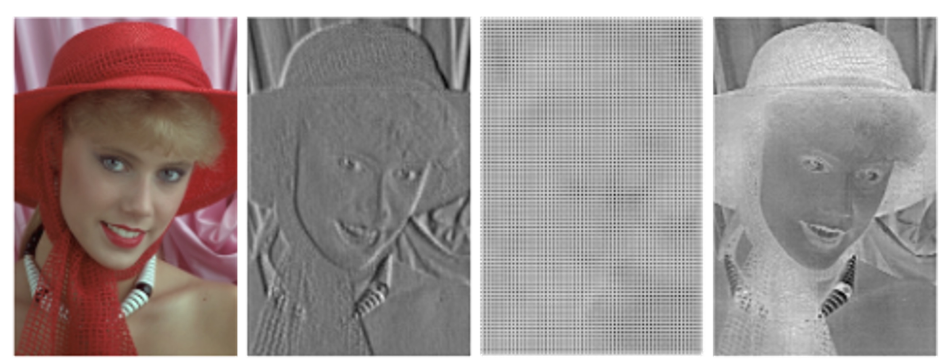


Fig. 5. PSNR on CLIC Test Dataset



(a) (b) (c) (d)

Fig. 6. Visualization for checkerboard artifacts comparison. (a) is the input image, while (b), (c) and (d) denote output feature maps of the transposed convolution layer, the transposed adder layer and the proposed AIP structure, respectively.

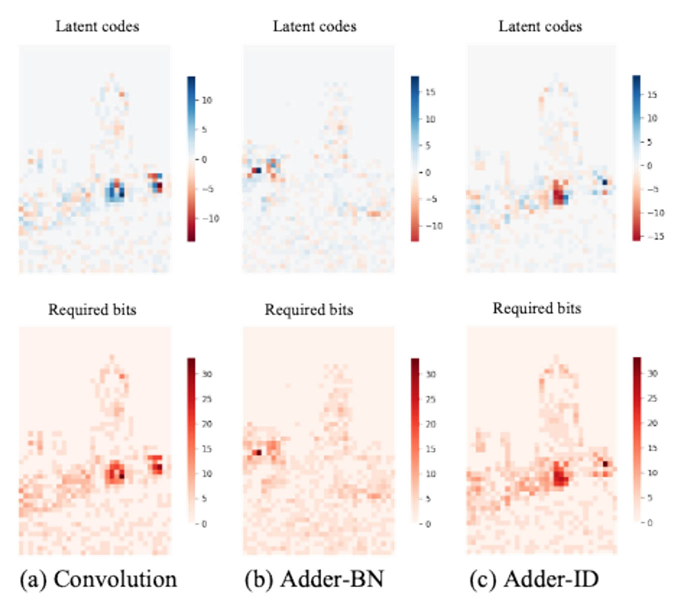


Fig. 3. Visualization of latent codes and redundancies.

Table 1. #Mul. FLOPs and energy cost of different networks.

Model	CNN	AdderIC	Reduction
Multiplication FLOPs	1.303G	0.255G	80.43%
Energy Cost (*pJ*)	5.994G	4.193G	30.05%

To verify the effectiveness of ID for reducing spatial redundancies, we visualize the latent codes and required bits of different architectures, including convolution, Adder-BN and the proposed Adder-ID. It is obvious that the conventional Adder-BN cannot effectively reduce spatial redundancies, while the proposed Adder-ID is able to efficiently capture useful information and significantly reduce pixel-wise redundancies, which is similar to the convolution layer.

To confirm the efficiency of AIP structure, we visualize the output feature maps of different upsampling structures in Fig. 6. The results show that the transposed adder layer can easily cause checkerboard artifacts, which would lead to poor reconstruction quality. By contrast, the proposed AIP structure as well as the transposed convolution can avoid them and maintain the details of the original images effectively.

At last, we compare the proposed AdderIC with its CNN counterpart in aspects of rate-distortion performance, along with computation cost and energy consumption. From Fig. 6, Fig. 4 and Fig. 5, we can see that our AdderIC model shows comparable performance to CNN-based architecture, and is better than other AdderNet structures. Besides, we omit the ID and k=1 convolution due to their low computation cost, and compare the multiplication FLOPs and energy cost between AdderIC and its CNN counterpart in Table 1. The results show that AdderIC reduces the multiplication FLOPs by approximately 80% and energy consumption by 30%.