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Pyramid Attention Network for Image Restoration

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Abstract
Self-similarity refers to the image prior widely used in image restoration algorithms that small but similar patterns tend to occur at different locations and scales. However, recent advanced deep convolutional neural network-based methods for image restoration do not take full advantage of self-similarities by relying on self-attention neural modules that only process information at the same scale. To solve this problem, we present a novel Pyramid Attention module for image restoration, which captures long-range feature correspondences from a multi-scale feature pyramid. Inspired by the fact that corruptions, such as noise or compression artifacts, drop drastically at coarser image scales, our attention module is designed to be able to *borrow* clean signals from their "clean" correspondences at the coarser levels. The proposed pyramid attention module is a generic building block that can be flexibly integrated into various neural architectures. Its effectiveness is validated through extensive experiments on multiple image restoration tasks: image denoising, demosaicing, compression artifact reduction, and super resolution. Without any bells and whistles, our PANet (pyramid attention module with simple network backbones) can produce state-of-the-art results with superior accuracy and visual quality. Our code is available at https://github.com/SHI-Labs/Pyramid-Attention-Networks

Keywords Image restoration · Image denoising · Demosaicing · Compression artifact reduction · Super-resolution

1 Introduction

Image restoration algorithms aim to recover a high-quality image from the contaminated counterpart, and is viewed as an ill-posed problem due to the irreversible degradation processes. They have many applications depending on the type of corruptions, for example, image denoising Zhang et al. (2017a, 2019); Liu et al. (2018), demosaicing Zhang et al. (2017b, 2019), compression artifacts reduction Dong et al. (2015); Chen and Pock (2017); Zhang et al. (2017a), super-resolution Kim et al. (2016); Lai et al. (2017); Tai et al. (2017) and many others Li et al. (2017); He et al. (2010); Chen et

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