Noisy Image Compression: A Comparison of Wavelets, Multiwavelets, Wavelet Packets, and Multiwavelet Packets

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Most wavelet-based image compression research to date has been limited to noiseless test images. This paper compares the behavior of the latest wavelet-based compression algorithms in the presence of noise. The analysis is comprehensive, employing all wavelet compression methods including scalar wavelets, multiwavelets, wavelet packets, and the novel multiwavelet packets. The performance of each of these methods depends on the image content; performance varies for natural and synthetic images and for high and low frequency content. State-of-the-art techniques are compared for: the wavelet filters and multiwavelet filters; the tree pruning cost functions; the multiwavelet decomposition method; and, the SPIHT-like quantization schemes. The comprehensive combination of test images, wavelet and filter combinations, and bit rates culminated in results based on 63,360 reconstructed images!

Comparing scalar wavelets and multiwavelets for both natural and synthetic images, multiwavelets performed better than scalar wavelets as the amount of noise increased. This is a departure from the noiseless image compression results for natural images where scalar wavelets consistently outperformed multiwavelets. Similarly, multiwavelet packets performed better than wavelet packets for noisy natural and synthetic images (whereas the wavelet packets were superior for natural images in the noiseless case). This behavior can be attributed to multiwavelets and multiwavelet packets’ ability to better capture high-frequency content than their scalar counterparts.

For multiwavelet-based image compression, we utilized a new quantization method called shuffling that allows multiwavelet decompositions to receive most of the benefits of using a quantizer like SPIHT. Although shuffling continued to be a significant source of improvement in the peak signal-to-noise ratios of reconstructed noisy images, the amount of improvement decreased with increasing noise levels. Figure 1 illustrates the shuffling improvement in the Gray 21 image corrupted by Gaussian noise.

![Figure 1](image.png)

**Fig. 1.** (a) Close-up of original Gray 21. (b) Close-up of corrupted Gray 21 using Gaussian noise at SNR=100dB compressed with SA4 multiwavelet without shuffling to 0.250 bpp, PSNR=36.03 dB. (c) Compressed with SA4 multiwavelet with shuffling to 0.250 bpp, PSNR=39.31 dB.