# Improving Inverse Wavelet Transform by Compressive Sensing Decoding with Deconvolution

Dong Liu[1], Xiaoyan Sun[2], and Feng Wu[2]
[1]University of Science and Technology of China, Hefei 230027, China
[2]Microsoft Research Asia, Beijing 100190, China
Email: liud@mail.ustc.edu.cn, xysun@microsoft.com, fengwu@microsoft.com

In this paper we propose an alternative decoding method for inverse wavelet transform when only partial coefficients are available. We have been inspired by the recently developed compressive sensing (CS) decoding, which is capable in recovering sparse signals from a few linear and non-adaptive measurements. Let $x$ be a sparse signal with $N$ entries and only $K$ out of them are non-zero, and $y$ be its approximation coefficients. Classic CS decoding such as $l_1$-minimization can be applied to decode $x$ from $y$, and it indeed provides better reconstruction of sparse signals than direct inverse transform, as demonstrated by our simulation results in Figure 1. When coefficients have been quantized, the performance of CS decoding decreases more severely compared with direct inverse transform, but still better than the latter once the signal is sparse enough.

We then consider the case of images. Since many natural images are not sparse, we propose to improve CS decoding from the Bayesian point of view, i.e., to incorporate natural image priors. Moreover, as wavelet transform can be described as convolution followed by down-sampling, such image priors can be integrated into the design of deconvolution or up-sampling. In case only the approximation coefficients are available, we present an iterative deconvolution method for CS decoding. Experimental results on some standard gray-scale images demonstrate the efficiency of our method. It achieves 0.82dB gain over direct inverse transform on the Lena image.

Our findings have immediate applications in wavelet-based compression systems, and also indicate a different approach to achieve sparse representation of natural images.

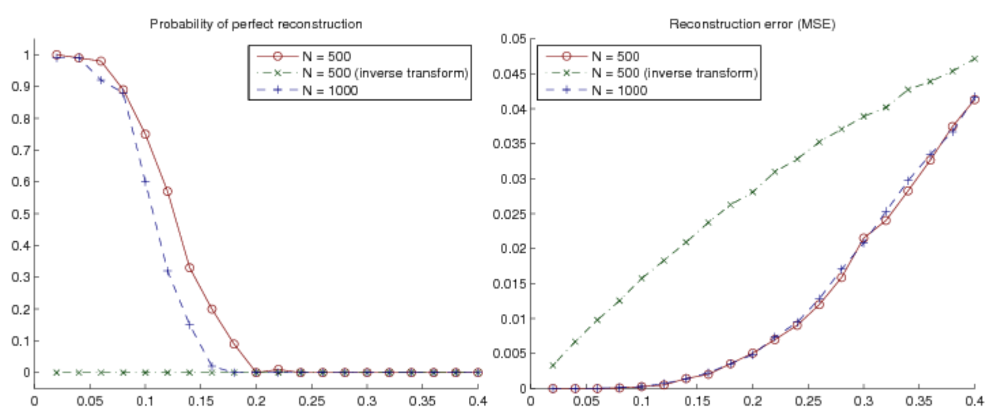


Figure 1. Simulation results on 1-D sparse signals. Left: probability of perfect reconstruction (defined as MSE value less than $10^{-4}$) versus signal sparsity; right: reconstruction MSE versus signal sparsity.

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