Sparse Coding and Trainable Algorithms for Inverse Imaging Problems

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Abstract

Sparse coding consists of representing signals as linear combinations of few dictionary elements that may be learned from data. Such a principle has been successfully used in the past as a prior on natural image patches for solving image restoration problems. These methods are however often outperformed by deep learning models, which are able to leverage pairs of corrupted/clean images for supervised learning. In this presentation, we present a line of work that combines traditional modelization from inverse imaging problem with automatic differentiation techniques, allowing to learn model parameters with supervision. This approach allows to use classical image priors such as sparsity and image self-similarities within trainable and interpretable architectures. We apply this approach to denoising, blind denoising, jpeg deblocking, and demosaicking, and show that its performance on several standard benchmarks is on par or better than state-of-the-art methods that may have an order of magnitude or more parameters.

References

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