UNROLLED MULTIPLICATIVE UPDATES FOR NONNEGATIVE MATRIX FACTORIZATION APPLIED TO HYPERSPECTRAL UNMIXING

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HyperSpectral Unmixing (HSU), the problem of separating mixed spectra of overlapping materials in a hyperspectral image, has motivated dedicated algorithmic developments in the last two decades. Traditional model-based algorithms frequently guarantee interpretable results. Deep-learning-based approaches are often faster at inference time and may obtain better empirical results. Our work [1] utilizes the strengths of both approaches by building on the deep unrolling paradigm. Precisely, HSU objective is to decompose the observed data matrix into *endmembers* and *abundances*. A classical approach is to solve the resulting nonnegative matrix factorization (NMF) problem using multiplicative updates (MU). Although MU is conceptually simple, it can empirically lead to spurious solutions. We propose to improve MU through deep algorithm unrolling while preserving its multiplicative structure and interpretability. For that, we introduce two architectures, *Non-Adaptive Learned Multiplicative Updates* (NALMU) and *Recursive Adaptive Learned Multiplicative Updates* (RALMU). NALMU introduces learned nonnegative acceleration matrices into the *endmember* update of MU. RALMU generalizes this for both *abundance* and *endmember* updates, by recursively predicting acceleration matrices from the current iterate through lightweight neural networks. Interestingly, for the non-blind HSU problem with tied acceleration weights, we further show that each NALMU endmember update can be associated with the decrease of an explicit cost function we provide. From an experimental point of view, NALMU and RALMU were evaluated on simulated astrophysical data and real hyperspectral remote-sensing scenes. They are competitive with other state-of-art HSU methods while being more interpretable. These results demonstrate that unrolling of multiplicative updates can combine the interpretability of model-based NMF (explicit cost function) with the adaptability of neural networks.
Reference toward the full article: [1] Kervazo, C., & Cohen, J. E. (2026). Unrolled multiplicative updates for nonnegative matrix factorization applied to hyperspectral unmixing.

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