Supplementary Materials: Hierarchical sparse nonnegative matrix factorization for hyperspectral unmixing with spectral variability

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This report provides complementary results in support of the paper [1]. Section 1 conducts an sensibility analysis of the proposed algorithm with respect to key parameters. Section 2 reports additional quantitative results for experiments conducted on the synthetic data sets SIM1 and SIM2 corrupted by a noise with a lower signal-to-noise-ratio (SNR).

1. Parameter sensitivity analysis

The sensitivity of the proposed HSNMF algorithm with respect (w.r.t.) the parameters S_1 and λ_a is illustrated in Fig. S1 in term of accuracy of abundance estimation (RMSE). As expected, a large value (i.e., ≈ 10) of λ_a leads to poor estimates of the abundances by imposing too much sparsity. For the SIM1 data set, a large value of S_1 results to bad esimation mainly because the clustering step fails. On the other hand, for the SIM2 data set, the HSNMF algorithm seems to be less sensitive w.r.t. the parameters. This can be explained by the fact this data set contains a large number of prototypal endmember spectra.

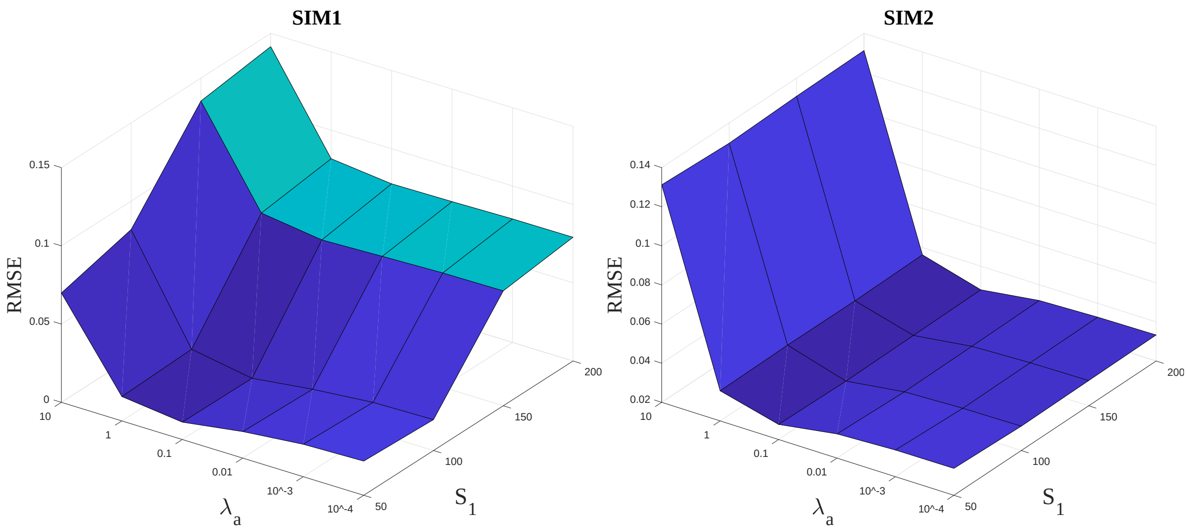

Figure S1. Sensitivity analysis of the proposed HSNMF w.r.t. the parameters λ_a and S_1.

2. Results obtained from a low SNR scenario

In [1], experiments are conducted with a noise level chosen as SNR= 30dB. Hereafter, we report results obtained for a wose case scenario by imposing a noise level of SNR= 20dB. Tables S1 and S2 provide the quantitative results for the SIM1 and SIM2 data sets, respectively. For SIM1 in this low SNR scenario, HSNMF performs better than compared methods except EBE-MEMM in terms of RMSE, SAM and JD. The good performance of EBE-MEMM can be explained by the fact this method is able to extract a larger number of endmember spectra within each class, thus reducing the impact of noise during the multiple endmember unmixing process. For SIM2, the proposed HSNMF outperforms other compared methods in terms of RMSE, SAM and JD. This shows that HSNMF is robust to low SNR when endmember variability is large.

Table S1. SIM1 (SNR= 20dB) – Quantitative results (best values in bold).

	C-SunSAL	ELMM	MEMMs	EBE-FL	EBE-MEMM	HSNMF
RMSE	0.0865	0.0377	0.0288	0.0432	**0.0198**	0.024
RE	0.0433	**0.0226**	0.0434	0.0293	0.0336	0.0345
SAM	0.0374	0.0311	0.0367	0.0214	**0.0210**	0.0229
JD	0.7132	0.6147	0.1287	0.5678	**0.1037**	0.1079
Time	**0.085**	92.2889	2.6762	5.574	4.7082	19.0501

Table S2. SIM2 (SNR= 20dB) – Quantitative results (best values in bold).

	C-SunSAL	ELMM	MEMMs	EBE-FL	EBE-MEMM	HSNMF
RMSE	0.2036	0.1502	0.112	0.1854	0.1125	**0.044**
RE	0.0598	**0.0331**	0.057	0.058	0.0564	0.0387
SAM	0.0767	0.0618	0.0759	0.0623	0.0743	**0.0337**
JD	0.5491	0.5266	0.1712	0.5009	0.1698	**0.0947**
Time	**0.2479**	237.3549	18.4855	4.4852	19.1069	606.1786

Reference

1. Uezato, T.; Fauvel, M.; Dobigeon, N. Hierarchical sparse nonnegative matrix factorization for hyperspectral unmixing with spectral variability. *Remote Sensing* **2020**.