

# SPATIAL ADAPTIVE LOW-RANK TENSOR FACTORIZATION FOR HYPERSPPECTRAL IMAGE UNMIXING

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Hyperspectral images are 3-dimensional data cubes with two spatial dimensions and one spectral dimension with hundreds of bands. If we consider changes through time of the same regions, that would add yet another dimension. In order to apply traditional signal processing algorithms, multidimensional arrays are scanned and unfolded usually along the spectral dimension. After post-processing for atmospheric effects, the resulting data set has  $N$  pixels by  $P$  spectral bands and considers every pixel an independent sample of the material. This treatment sometimes ignores spatial relationships amongst neighboring pixels that could be useful for further dimensionality reduction or endmember identification and classification in the case where signal unmixing is applied. In this investigation, we explore the use of tensor decompositions for hyperspectral unmixing (HU) on benchmark data sets. Canonical Polyadic Decomposition (CPD) decomposes a tensor  $T \in \mathbb{R}^{M \times N \times P}$  into a sum of  $R$  tensors each of which is the outer product of three vectors. We use the highest values of component vectors associated with the spatial dimensions to identify regions where candidate endmembers may lie. Then spectral unmixing is done by applying fully constrained least squares (FCLS), given a set of endmembers. Low-rank  $(L_R, L_R, 1)$  is a generalization of CPD which decomposes a tensor into a sum  $R$  tensors as CPD, but each component is the outer product of an  $L_R$ -rank matrix and a vector, where  $L_R > 1$ . This framework allows for increased spatial resolution of each component. We compare results of CPD and  $(L_R, L_R, 1)$  decomposition against traditional Non-negative Matrix factorization and show a performance improvement for  $(L_R, L_R, 1)$ . An improvement against other non-tensor approaches is also observed.

