

Abstract

- Convolutional Sparse Coding (CSC) has gained attention for its successful role as a reconstruction and a classification tool.
- Current CSC methods can only reconstruct single feature 2D images independently.
- However, examining correlations among all the data jointly is very important and should be considered for reconstruction applications.
- In this paper, we propose a generic and novel formulation for the CSC problem that can handle an arbitrary order tensor of data.

The CSC problem

$$\min_{\mathbf{x}_k, \mathbf{d}_k} \frac{1}{2} \sum_n \|\mathbf{y}_n - \sum_k \mathbf{d}_k * \mathbf{x}_k^n\|_2^2 + \lambda \sum_k \|\mathbf{x}_k^n\|_1$$

s.t. $\|\mathbf{d}_k\|_2^2 \leq 1 \quad \forall k = 1, \dots, K$

The t-SVD Decomposition

$$\text{circ}(\mathcal{A}) = \begin{bmatrix} \mathbf{A}^{(1)} & \mathbf{A}^{(n_3)} & \dots & \mathbf{A}^{(2)} \\ \mathbf{A}^{(2)} & \mathbf{A}^{(n_1)} & \dots & \mathbf{A}^{(3)} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{(n_3)} & \mathbf{A}^{(n_3-1)} & \dots & \mathbf{A}^{(1)} \end{bmatrix}$$

$\mathcal{A} \in \mathbb{R}^{n_1 \times n_2 \times n_3}$ $\mathcal{B} \in \mathbb{R}^{n_2 \times n_3 \times n_4}$ $\mathcal{Z} = \mathcal{A} \otimes \mathcal{B} = \text{fold}(\text{circ}(\mathcal{A}) \text{MatVec}(\mathcal{B}))$

such that: $\mathcal{Z}(i, j, :) = \sum_{k=1}^{n_2} \mathcal{A}(i, k, :) \otimes \mathcal{B}(k, j, :) \quad \forall i, j$

3rd-order Tensor (1-D CSC)

$$\min_{\mathcal{D}, \vec{\mathcal{X}}} \frac{1}{2} \sum_n \|\vec{\mathcal{Y}}_n - \mathcal{D} \otimes \vec{\mathcal{X}}_n\|_F^2 + \lambda \|\vec{\mathcal{X}}_n\|_{1,1,1}$$

s.t. $\|\vec{\mathcal{D}}_k\|_F^2 \leq 1 \quad \forall k = 1, \dots, K$

N-order tensor CSC (N-D CSC)

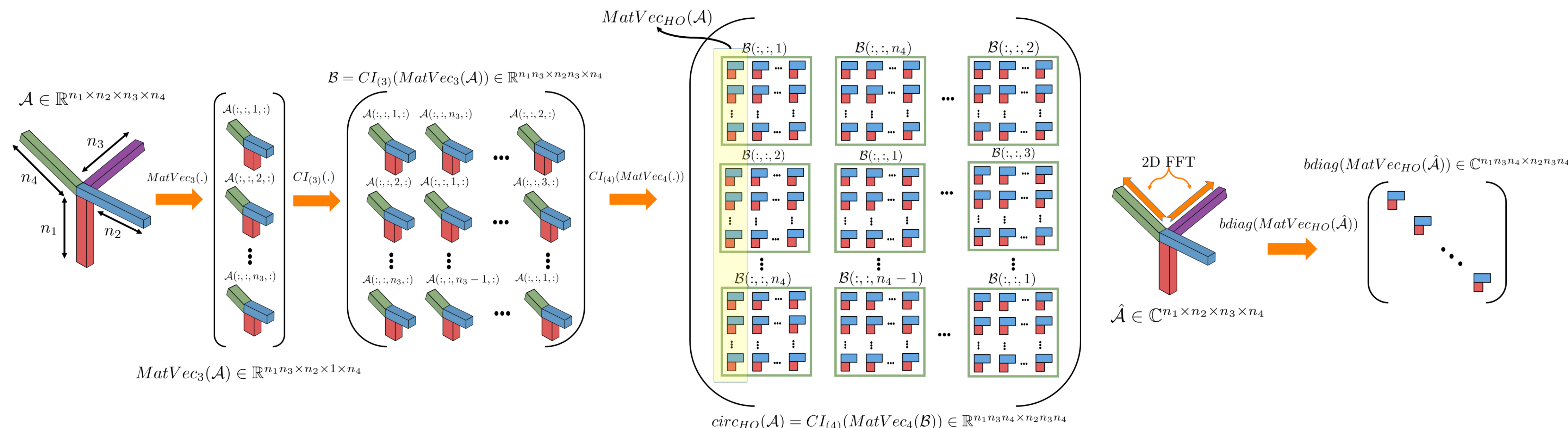
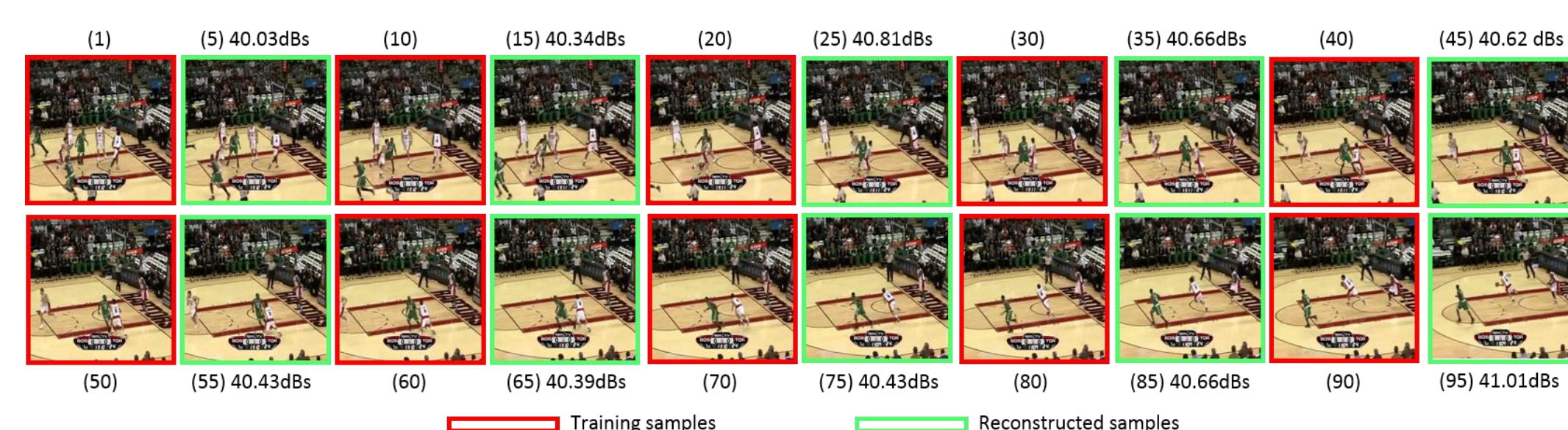
$\vec{\mathcal{Y}}_n \in \mathbb{R}^{n_1 \times 1 \times n_2 \times \dots \times n_d}$

The K filters $\{\vec{\mathcal{D}}_i\}_{i=1}^K$ $\mathcal{D} \in \mathbb{R}^{n_1 \times K \times n_2 \times \dots \times n_d}$

The n^{th} sparse code is $\vec{\mathcal{X}}_n \in \mathbb{R}^{K \times 1 \times n_2 \times \dots \times n_d}$

Definition 3.1 (High Order t-products):

$$\mathcal{D} \otimes_{HO} \vec{\mathcal{X}} = \text{fold}_{HO}(\text{circ}_{HO}(\mathcal{D}) \text{MatVec}_{HO}(\vec{\mathcal{X}}))$$



$$\min_{\mathcal{D}, \vec{\mathcal{X}}} \frac{1}{2} \sum_n \|\vec{\mathcal{Y}}_n - \mathcal{D} \otimes_{HO} \vec{\mathcal{X}}_n\|_F^2 + \lambda \|\vec{\mathcal{X}}_n\|_{1, \dots, 1}$$

s.t. $\|\vec{\mathcal{D}}_k\|_F^2 \leq 1 \quad \forall k = 1, \dots, K$

$$\text{circ}_{HO}(\mathcal{D}) = (\mathbf{F}_{n_d} \otimes \mathbf{F}_{n_{d-1}} \otimes \dots \otimes \mathbf{F}_{n_2} \otimes \mathbf{I}_{n_1})$$

$$\text{bdiag}(\text{MatVec}_{HO}(\hat{\mathcal{D}}))(\mathbf{F}_{n_d} \otimes \mathbf{F}_{n_{d-1}} \otimes \dots \otimes \mathbf{F}_{n_2} \otimes \mathbf{I}_K)^H$$

ADMM Solver

Subproblem (1): Sparse Coding.

$$\arg \min_{\vec{\mathcal{X}}, \vec{\mathcal{Z}}} \frac{1}{2} \|\vec{\mathcal{Y}} - \mathcal{D} \otimes_{HO} \vec{\mathcal{X}}\|_F^2 + \lambda \|\vec{\mathcal{Z}}\|_{1, \dots, 1}$$

s.t. $\vec{\mathcal{X}} = \vec{\mathcal{Z}}$

$$\frac{1}{2} \|\vec{\mathcal{Y}} - \mathcal{D} \otimes_{HO} \vec{\mathcal{X}}\|_F^2 = \frac{1}{2} \|\text{MatVec}_{HO}(\vec{\mathcal{Y}}) - \text{bdiag}(\text{MatVec}_{HO}(\hat{\mathcal{D}})) \text{MatVec}(\vec{\mathcal{X}})\|_F^2$$

$$\hat{\mathcal{X}}^{(i)} \leftarrow \arg \min_{\hat{\mathcal{X}}^{(i)}} \frac{1}{2} \|\hat{\mathcal{D}}^{(i)} \hat{\mathcal{X}}^{(i)} - \hat{\mathcal{Y}}^{(i)}\|_2^2 + \frac{\rho_1}{2} \|\hat{\mathcal{X}}^{(i)} - \hat{\mathcal{Z}}^{(i)}\|_2^2$$

$+ \langle \hat{\mathcal{U}}^{(i)}, \hat{\mathcal{X}}^{(i)} \rangle$

$$\hat{\mathcal{X}}^{(i)} \leftarrow (\hat{\mathcal{Y}}^{(i)} \hat{\mathcal{X}}^{(i)\top} + \rho_2 \hat{\mathcal{T}}^{(i)} - \hat{\mathcal{G}}^{(i)}) (\hat{\mathcal{X}}^{(i)} \hat{\mathcal{X}}^{(i)\top} + \rho_2 \mathbf{I}_K)^{-1}$$

$$\vec{\mathcal{Z}} \leftarrow \arg \min_{\vec{\mathcal{Z}}} \frac{\lambda}{\rho_1} \|\vec{\mathcal{Z}}\|_{1, \dots, 1} + \frac{\rho_1}{2} \|\vec{\mathcal{Z}} - \left(\vec{\mathcal{X}} + \frac{\vec{\mathcal{U}}}{\rho_1} \right)\|_F^2$$

$$\vec{\mathcal{U}} \leftarrow \vec{\mathcal{U}} + \rho_1 (\vec{\mathcal{X}} - \vec{\mathcal{Z}})$$

Table 1: Reconstruction error using TCSC trained with $\lambda = 20$ and an average sparsity of 64% across all 29 test samples for different values of K (number of filters in the dictionary).

K	20	40	60	80	100
dBs	70.63	94.45	98.35	104.43	104.70
Avg Sparsity(%)	63.93	64.00	66.66	60.73	65.43

Subproblem (2): Dictionary Learning.

$$\arg \min_{\mathcal{D}, \vec{\mathcal{Z}}} \frac{1}{2} \|\vec{\mathcal{Y}} - \mathcal{D} \otimes_{HO} \vec{\mathcal{X}}\|_F^2$$

s.t. $\vec{\mathcal{D}} = \vec{\mathcal{T}}, \quad \|\mathcal{T}_k\|_F^2 \leq 1 \quad \forall k$

$$\hat{\mathcal{D}}^{(i)} \leftarrow \arg \min_{\hat{\mathcal{D}}^{(i)}} \frac{1}{2} \|\hat{\mathcal{D}}^{(i)} \hat{\mathcal{X}}^{(i)} - \hat{\mathcal{Y}}^{(i)}\|_2^2 + \frac{\rho_2}{2} \|\hat{\mathcal{D}}^{(i)} - \hat{\mathcal{T}}^{(i)}\|_2^2$$

$+ \langle \hat{\mathcal{G}}^{(i)}, \hat{\mathcal{D}}^{(i)} \rangle$

$$\hat{\mathcal{D}}^{(i)} \leftarrow (\hat{\mathcal{Y}}^{(i)} \hat{\mathcal{X}}^{(i)\top} + \rho_2 \hat{\mathcal{T}}^{(i)} - \hat{\mathcal{G}}^{(i)}) (\hat{\mathcal{X}}^{(i)} \hat{\mathcal{X}}^{(i)\top} + \rho_2 \mathbf{I}_K)^{-1}$$

$$\hat{\mathcal{T}} \leftarrow \arg \min_{\hat{\mathcal{T}}} \frac{\rho_2}{2} \|\hat{\mathcal{T}} - \left(\hat{\mathcal{D}} + \frac{1}{\rho_2} \hat{\mathcal{G}} \right)\|_F^2$$

s.t. $\|\hat{\mathcal{T}}_i \times_p \Psi \times_q \Gamma\|_F^2 \leq 1 \quad \forall i = 1, \dots, K$

$$\hat{\mathcal{G}} \leftarrow \hat{\mathcal{G}} + \rho_2 (\hat{\mathcal{D}} - \hat{\mathcal{T}})$$

Experiments

