# Signal Recovery on Incoherent Manifolds

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Audio click removal



- Audio click removal
- Morphological Components Analysis (MCA)



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- Background subtraction in video



- Audio click removal
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- ...
- Numerous models have been explored
  - Spikes and sines
  - Points and lines
  - "Robust" compressive recovery
  - Low-rank + sparse matrices

#### Goal:

Solve **all** such signal recovery problems in a unified, computationally efficient, stable framework

#### Signal Recovery on Manifolds



Question asked (and answered) by several people [CRT06, Don06, FRP07, BD09, BCDH10, ..., SC11]

### Multi-Manifold Model

• Signal of interest:



• Noisy linear measurements:

$$y = \Phi x + e = \Phi(a^* + b^*) + e$$





Manifold incoherence



- Local vs. global incoherence

• Restricted isometry



$$1 - \delta \le \frac{\|\Phi(x_1 - x_2)\|^2}{\|x_1 - x_2\|^2} \le 1 + \delta$$

Projections onto manifolds



#### Projections onto manifolds

– Manifold of *K*-sparse signals

 $\mathcal{P}_{\mathcal{M}}(\mathbf{x}) = \mathbb{T}(\mathbf{x}, K)$ 

– Manifold of rank-r matrices

 $X = U\Sigma V$  $\mathcal{P}_{\mathcal{M}}(X) = U_r \Sigma_r V_r$ 

- Articulation Manifold (AM)  $\widehat{\theta} = \arg \max \langle X, \theta(X_0) \rangle$  $\mathcal{P}_{\mathcal{M}} = \widehat{\theta}(X_0)$ 







## Successive Projections onto Incoherent Manifolds (SPIN)

**Goal**: given  $y = \Phi(a^* + b^*) + e$ , recover  $(a^*, b^*)$ Initialize

 $a_0=0, \ b_0=0$ Iterate:

$$- \qquad a_{k+1} \leftarrow \mathcal{P}_{\mathcal{A}}(a_k + \eta \Phi^T(y - \Phi(a_k + b_k))) \\ - \qquad b_{k+1} \leftarrow \mathcal{P}_{\mathcal{B}}(b_k + \eta \Phi^T(y - \Phi(a_k + b_k)))$$

until convergence

[HB12]

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[HB12]

#### "Projected Block-Coordinate Descent"

## Convergence

Suppose that the *restricted isometry* constant of the sampling matrix relates to the manifold *incoherence* as:  $0 < \delta < \frac{1 - 11\epsilon}{1 - 11\epsilon}$ 

$$0 \le \delta < \frac{1 - 11\epsilon}{3 + 7\epsilon}$$

Then, for any precision parameter  $\nu$ , after a finite number of iterations of SPIN, we have:

$$\max\{\left\|\mathbf{a}_{k}-\mathbf{a}^{*}\right\|,\left\|\mathbf{b}_{k}-\mathbf{b}^{*}\right\|\}\leq\nu$$

#### Proof approach:

Define the residual error as  $\psi(a,b) = \frac{1}{2} \|y - \Phi(a+b)\|^2$ . We can show the following iteration invariant:  $\psi(a_{k+1}, b_{k+1}) \le \alpha \psi(a_k, b_k) + C \|e\|^2$ 

 $\alpha < 1 \implies$  convergence!

## Example: Spikes and Sines

• SPIN (provably) recovers the components of the linear sum of  $K_1$  spikes and  $K_2$  sines provided:

$$K_1+K_2 < \frac{1}{11\mu} \approx 0.091 \sqrt{N}$$

• Optimal bound for  $\ell_1$  -minimization

$$K_1 + K_2 < 0.91\sqrt{N}$$
 [EB02,FN03]

#### Constant can potentially be improved

## Example: Articulation Manifolds

- Signal size: N = 64 x 64 = 4096, number of measurements: M = 50
- Noise added to the signal



• Near-perfect recovery for M/N = 1.2% meas.!

# Example: Matrix Decomposition

• Low-rank + sparse model



- Efficient projection operators exist for both manifolds
- But (global) incoherence assumption is violated
  - there exist low-rank matrices that are sparse + vice versa

### Numerical Comparison

- Parameters:  $N = 128 \times 128$ , K = 164, r = 2
- Test matrices generated at random (100 trials)



-SPIN outperforms Compressive PCP, SpaRCS

[WGMM12,WSB11]

# Summary

- SPIN: unified framework for signal separation, multi-manifold recovery
- Highlights:
  - efficiency
  - provable convergence
  - conceptually simple: can be extended to more complex models, more than 2 manifolds, etc.
- Applications to MCA, signal/image denoising, background-foreground subtraction, etc.

### References

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