Towards Compressive Geospatial Sensing Via Fusion of LIDAR and Hyperspectral Imaging

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Challenges in Geospatial Representation and Compression

- Modern geospatial databases contain large amounts of multimodal data.
- Traditionally, each sensing modality is compressed independently.
- In particular, geometric compression of LIDAR point clouds depends on **decomposition of coarse surface components** [Samet & Kochut 2002, Wang & Tseng 2004, McDaniel et al. 2010].

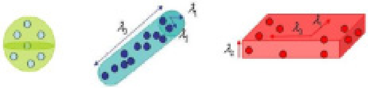


Figure: Point Scatters, Lines, Planes.

- Such decomposition by LIDAR points alone is a chichen-and-egg problem.

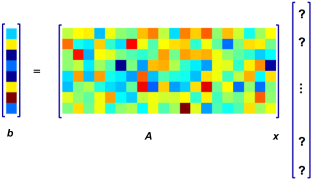
Compressive Geospatial Sensing via Sensor Fusion

- **Better compression offline:** Improving classification, innovation detection, and alignment of terrain attributes/surface components.
- **Compressive sensing:** Increase the speed of recognition and registration (real-time)?

Compressive Sensing Theory: An Introduction

- Compressive Sensing (CS) deals with an estimation problem in **underdetermined systems** of linear equations

$$\mathbf{b} = A\mathbf{x} \quad \text{where } A \in \mathbb{R}^{d\times n}, (d < n)$$

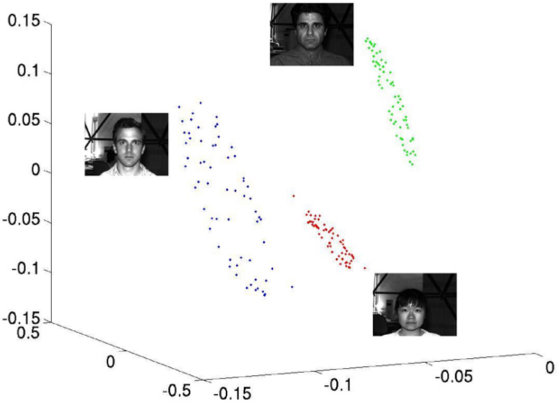


- Two interpretations:
  1. Compression: A as a sensing matrix.
  2. Sparse Representation: A as a prior dictionary.
- ℓ_1-Minimization (**Linear Program**)

$$\mathbf{x}^* = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subj. to } \mathbf{b} = A\mathbf{x}.$$

$$\|\mathbf{x}\|_1 = |x_1| + |x_2| + \cdots + |x_n|.$$

Robust Face Recognition



Classification of Mixture Subspace Model

1. Face-subspace model: Assume **b** belongs to Class i in K classes.

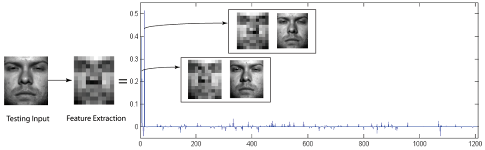
$$\begin{aligned} \mathbf{b} &= \alpha_{i,1}\mathbf{v}_{i,1} + \alpha_{i,2}\mathbf{v}_{i,2} + \cdots + \alpha_{i,n_1}\mathbf{v}_{i,n_i}, \\ &= A_i \alpha_i, \end{aligned}$$

   where $A_i = [\mathbf{v}_{i,1}, \mathbf{v}_{i,2}, \cdots, \mathbf{v}_{i,n_i}]$.

2. Nevertheless, Class i is the **unknown label** we need to solve:

   Sparse representation $\mathbf{b} = [A_1, A_2, \cdots, A_K] \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_K \end{bmatrix} = A\mathbf{x}.$

3. $\mathbf{x}^* = [\,0 \cdots 0 \;\alpha_i^T\; 0 \cdots 0\,]^T \in \mathbb{R}^n.$



Sparse representation $\mathbf{x}^*$ encodes membership!

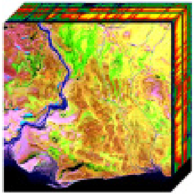
Demo

Demo I: Misalignment & Corruption Correction

- J. Wright, et al. *Robust Face Recognition via Sparse Representation*. IEEE PAMI, 2009.
- *Recognition via High-Dimensional Data Classification*. US patent, 2009. Int. patent, 2010.
- *Face Recognition Breakthrough*, Comm. of the ACM, 2010.

Demixing Hyperspectral Measurements

- A hyperspectral image contains $d > 200$ spectral bands.



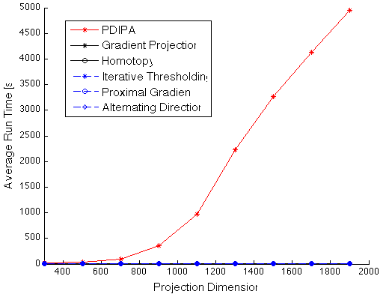
- Each hyperspectral pixel is capable of differentiating finer surface attributes i.e. **sand, grass, concrete, ocean**.
- Demixing a hyperspectral pixel is modeled by a mixture linear model [Keshave & Mustard 2002, Zymnis et al. 2007]:

$$\begin{aligned}\mathbf{b} &= [A_1, A_2, \cdots, A_C]\mathbf{x} \\ &= A\mathbf{x}\end{aligned}$$

- Sparse coefficients in $\mathbf{x}$ reveal the mixing parameters for the pixel $\mathbf{b}$.

Fast ℓ_1-minimization is still a difficult problem!

- General toolboxes do exist: **cvx**, **SparseLab**.
  However, interior-point methods are **very** expensive in HD space.



References

1. **Primal-Dual Interior-Point** Methods
   - Log-Barrier [Frisch 1955, Karmarkar 1984, Megiddo 1989, Monteiro-Adler 1989, Kojima-Megiddo-Mizuno 1993]
2. **Homotopy** Methods:
   - Homotopy [Osborne-Presnell-Turlach 2000, Malioutov-Cetin-Willsky 2005, Donoho-Tsaig 2006]
   - Polytope Faces Pursuit (PFP) [Plumbley 2006]
   - Least Angle Regression (LARS) [Efron-Hastie-Johnstone-Tibshirani 2004]
3. **Gradient Projection** Methods
   - Gradient Projection Sparse Representation (GPSR) [Figueiredo-Nowak-Wright 2007]
   - Truncated Newton Interior-Point Method (TNIPM) [Kim-Koh-Lustig-Boyd-Gorinevsky 2007]
4. **Iterative Thresholding** Methods
   - Soft Thresholding [Donoho 1995]
   - Sparse Reconstruction by Separable Approximation (SpaRSA) [Wright-Nowak-Figueiredo 2008]
5. **Proximal Gradient** Methods [Nesterov 1983, Nesterov 2007]
   - FISTA [Beck-Teboulle 2009]
   - Nesterov's Method (NESTA) [Becker-Bobin-Candés 2009]
6. **Augmented Lagrange Multiplier** Methods [Yang-Zhang 2009, Yang et al 2010]
   - YALL1 [Yang-Zhang 2009]
   - Primal ALM, Dual ALM [Yang 2010]

References:

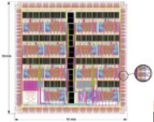
Yang, *et al.*, *A review of fast ℓ_1-minimization algorithms for robust face recognition*. Submitted to SIAM Imaging Sciences, 2010.

Demo II: Speed of ℓ_1-Min Solvers

Ongoing development at Berkeley

- An open-source ℓ_1-min library in MATLAB.
  `http://www.eecs.berkeley.edu/~yang/software/l1benchmark/`
- Investigate parallelization using many-core CPUs/GPUs.

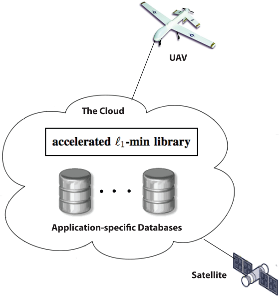
- Collaboration with industry to develop cloud services for general ℓ_1-minimization.
  (in collaboration with a startup)



Technical Approach

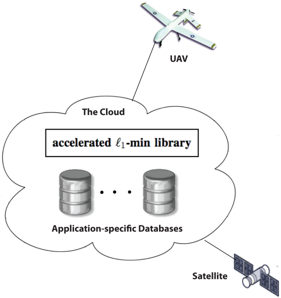
1. Improving classification of terrain attributes via sparse representation.

2. **Compressive geospatial sensing:** Improving real-time performance of large-scale data.



3. Improving compression of 3-D point cloud via hybrid geometric representation. [Zakhor]

Compressive Geospatial Sensing via Sensor Fusion



1. Aerial vehicle equipped with multiple sensing modalities.
2. Different sensing modalities must be properly aligned in terms of the 3D coordinates.
3. Online classification of terrain attributes "on the fly."
4. Hybrid geometric models to effectively represent the 3-D geo-structures.

What we want to see:

1. **Standard, Open-Source Geospatial Databases** to the public for research purposes.
2. **Industrial Partnerships** that have the resources for geospatial data acquisition and system implementation.

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