Pre-processing and Classification of Hyperspectral Imagery via Selective Inpainting

Victoria Chayes, Kevin Miller, Rasika Bhalerao, Jiajie Luo, Wei Zhu, Andrea L. Bertozzi, Wenzhi Liao, Stanley Osher

University of California, Los Angeles

6 March 2017

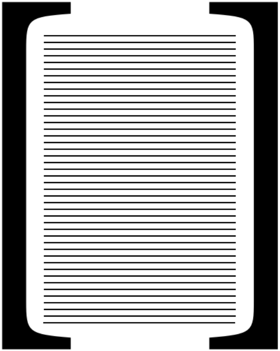
The Concept

Semi-Supervised Classification model using Selective Pixel Removal and APGL Inpainting.

1. Hand-Select/work with pre-known endmembers.
2. Using a PCA scheme, remove parts of pixels that are not within a threshold distance of an endmember.
3. Using APGL and a modified APGL algorithm for matrix completion, reconstruct the hyperspectral image
4. Classification can now be done for each pixel using the direct Euclidean distance from the endmembers

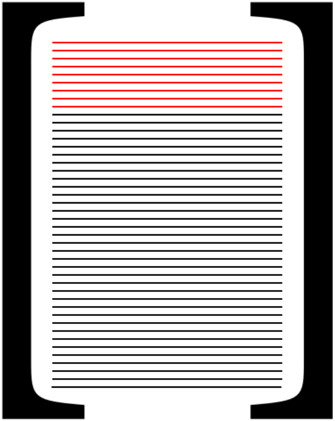
PCA Initialization

1. Order the pixels (rows) based on distance to nearest endmember.
2. Order bands (columns) of each pixel pseudo-randomly based on top PCA bands.



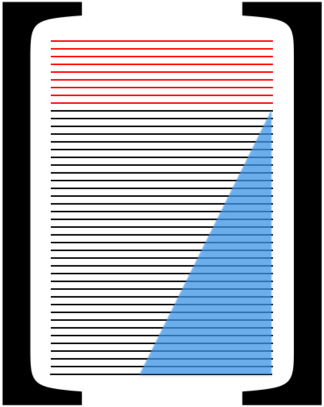
PCA Initialization

2. Top 20% is kept as index set.



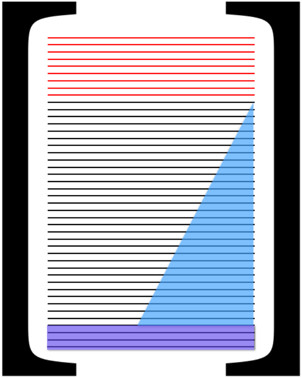
PCA Initialization

2. Top 20% is kept as index set.
3. Lower [x]% is cut (adjustable to dataset).

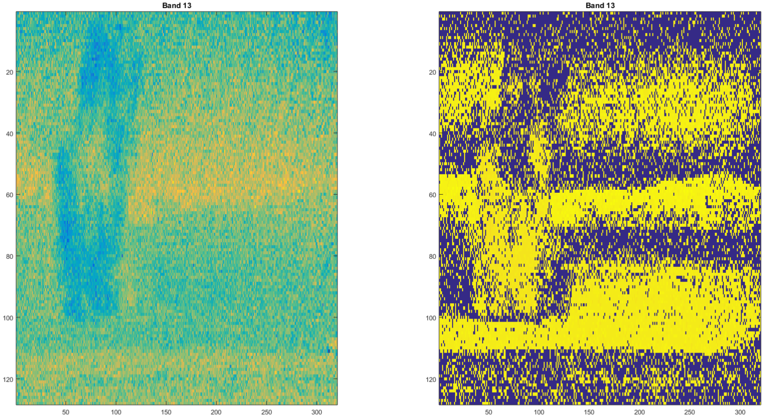


PCA Initialization

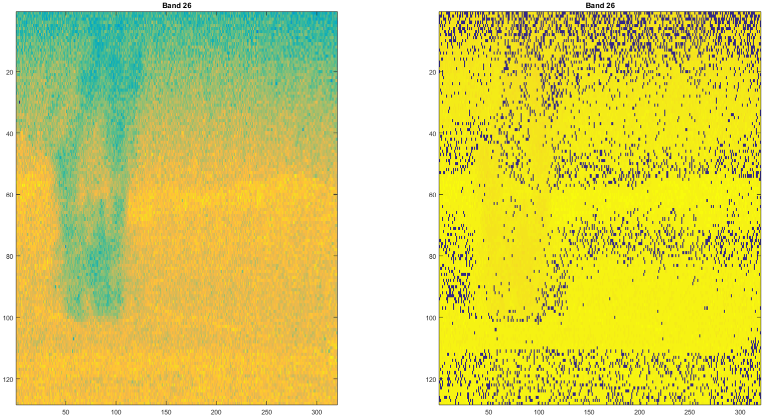
2. Top 20% is kept as index set.
3. Lower [x]% is cut (adjustable to dataset).



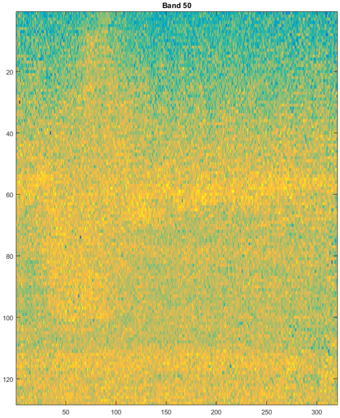
PCA Initialization-Band by Band

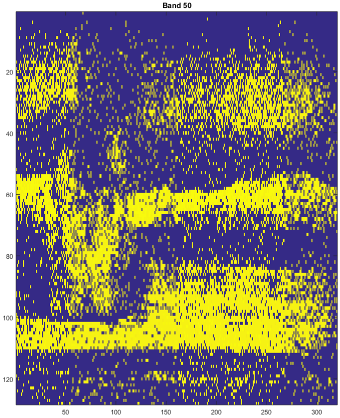


PCA Initialization-Band by Band



PCA Initialization-Band by Band





APGL: Original Algorithm

1. The APGL (Accelerated Proximal Gradient with Linesearch) algorithm minimizes a problem of the form:

$$\arg\min_{X} \quad \frac{1}{2}||\mathcal{A}(X) - b||_2^2 + \mu||X||_*$$

2. $\mathcal{A}$ is a linear operator that can be thought of as the index set from X, the original image that we're trying to reconstruct, to b, the partial image that we observe.
3. Minimizing the rank of X corresponds to the stipulation that each pixel is the linear combination of a small set of endmembers.

APGL-Hyp Algorithm

1. Add a penalization term for distance of inpainted pixels from endmembers.
2. Instead of minimizing:

$$\arg\min_X \quad \frac{1}{2}||\mathcal{A}(X) - b||_2^2 + \mu||X||_*$$

we minimize

$$\arg\min_X \quad \frac{1}{2}||\mathcal{A}(X) - b||_2^2 + \mu||X||_* + \frac{\lambda}{2}||X - CX||_F^2$$

where "CX" is a projection of each pixel onto the nearest endmember.

APGL Algorithm: Proximal Gradient Method

- Solve a minimization problem of the form:

$$F(X) = f(X) + P(X)$$

- P is proper, convex, lower, semicontinuous: $||X||_*$ is an acceptable P.
- f is convex, smooth, and continuously differentiable on domP
- Use iterative interpolation:

$$\begin{cases} X^k = S_{\tau^k}(G^k) \\ G^{k+1} = X^k - (\tau^k)^{-1}\mathcal{A}^*(\mathcal{A}(X^k) - b) \end{cases}$$

APGL Hyperspectral Algorithm

APGL_Hyp Algorithm

1. Let $\mu > 0$ be a fixed regularization parameter, let $\eta \in (0,1)$ be a given constant. Let $X^0 = X^1 = 0 \in \mathbb{R}^{m\times n}$, let $t^0 = t^{-1} = 1$ and let $\tau^0 = 1 + \lambda$.

2. Repeat the following loop until convergence: for $k = 0, 1, 2, \dots$, generate X^{k+1} according to the following iteration:

   (a) Set $Y^k = X^k + \frac{t^{k-1}-1}{t^k}(X^k - X^{k-1})$

   (b) Calculate CX^{k-1}.

   (c) Set $\widehat{\tau}_0 = \eta\tau^{k-1}$

   (d) For j=0, 1, 2, ...

   Set $G = Y^k - (\widehat{\tau}_j)\mathcal{A}^*(\mathcal{A}(Y^k) - b) + \lambda(X^k - CX^{k-1})$.

   Compute $S_{\widehat{\tau}_j}(G) = U\mathrm{Diag}(\sigma - \mu/\widehat{\tau}_j)_+ V^T$

   If $F(S_{\widehat{\tau}_j}(G)) \leq Q_{\widehat{\tau}_j}(S_{\widehat{\tau}_j}(G))$,

   Set $\tau^k = \widehat{\tau}_j$, break

   Else,

   Set $\widehat{\tau}_{j+1} = \min\{\eta^{-1}\widehat{\tau}_j, \tau^0\}$

   end

   end

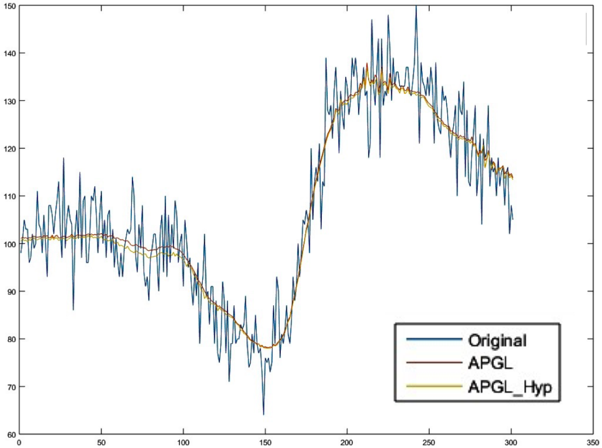
   (e) Set $X^{k+1} = S_{\tau)^k}(G)$

   (f) Set $t^{k+1} = \frac{1+\sqrt{1+4(t^k)^2}}{2}$.

Datasets

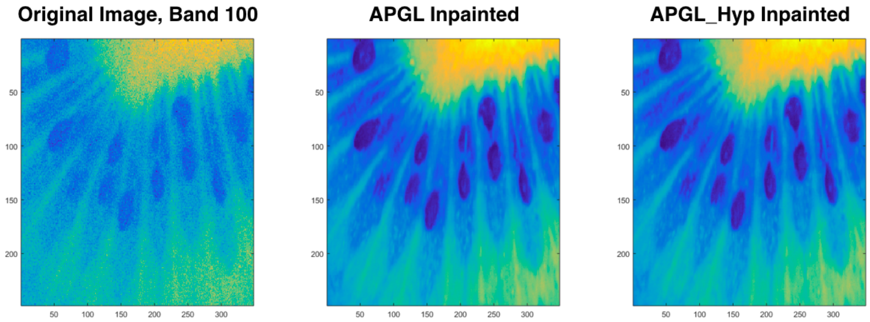
1. Kiwi Dataset
   - Close-up on a kiwi fruit, taken using a Specim AISA Hyperspectral Sensor.
   - original image 848 bands of wavelengths between 391.52 and 1007.37 nm taken from 0.7 to 0.76 nanometers apart, we worked with bands 250 to 449
   - 250 x 351 x 200
2. Chemical Plume Dataset
   - Chemical plume imaged from long wave infrared spectrometers placed 2km away by the John Hopkins University Applied Physics Laboratory
   - 128 x 320 x 129
3. Salinas-A Dataset
   - subscene of the Salinas dataset, taken by the AVIRIS sensor over Salinas Valley
   - 86 x 83 x 204

Pixel-Smoothing

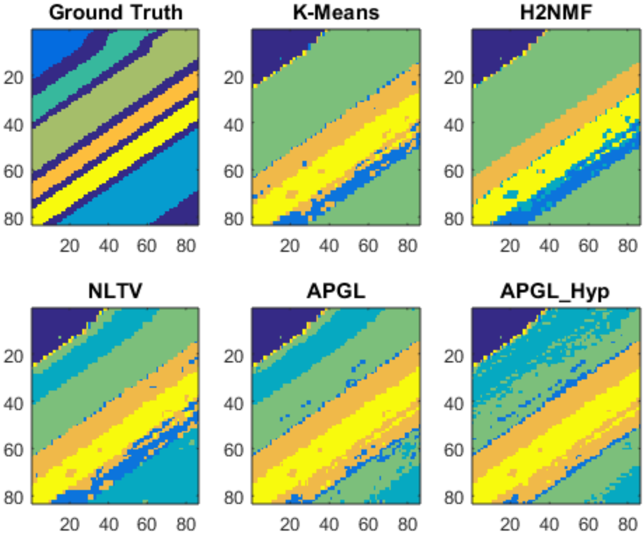


Pictured above: comparison of a pixel from the Kiwi Dataset with the same pixel from the APGL and APGL-Hyp sharpened datacube.

Band-by-Band Sharpening



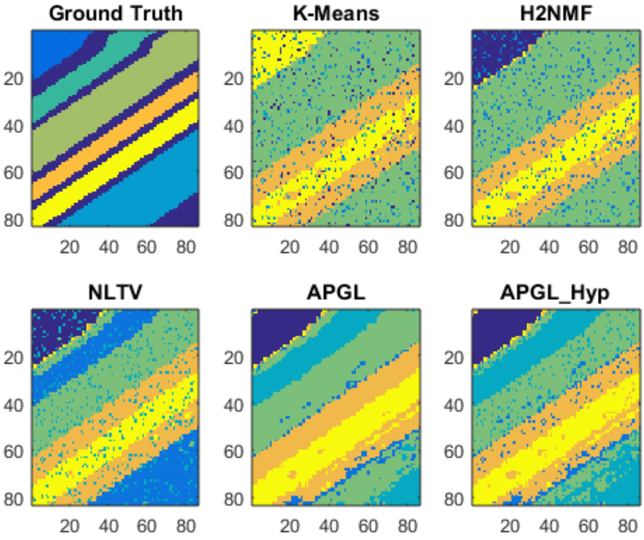
Salinas-A Dataset



Salinas-A Dataset

Algorithm	**Time**	**Accuracy**
K-Means	1.04	69.52 %
H2NMF	2.41	70.08 %
NLTV	53.83	80.42 %
APGL	29.98	76.93 %
APGL_Hyp	65.95	69.60 %

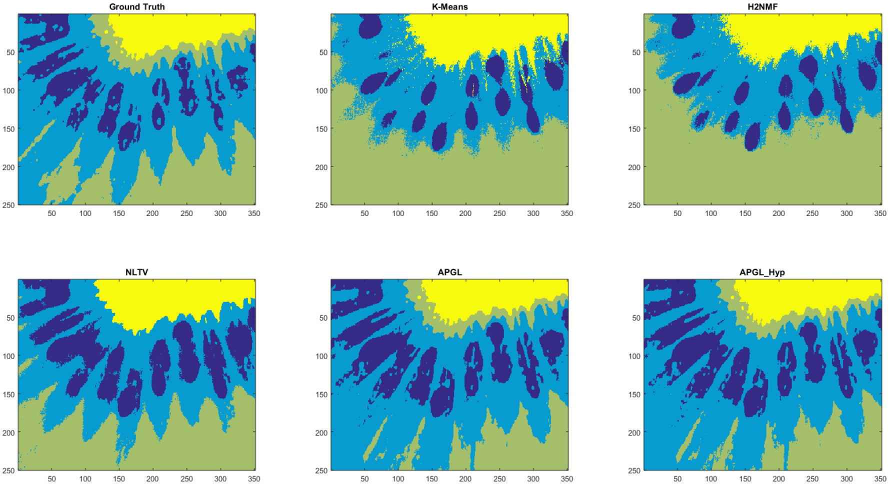
Salinas-A Dataset: 10 % Pixels Replaced



Salinas-A Dataset: 10% Pixels Replaced

Algorithm	**Time**	**Prior Accuracy**	**Accuracy 10% Replaced**
K-Means	4.60	69.55%	50.90%
H2NMF	1.75	70.08 %	58.36%
NLTV	54.23	80.42%	71.02%
APGL	33.57	76.93 %	76.78 %
APGL_Hyp	77.73	69.60%	72.57%

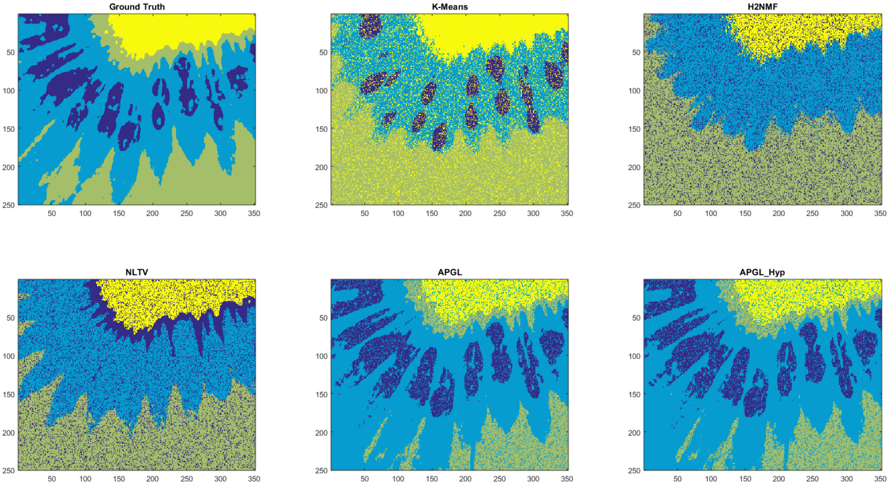
Kiwi Dataset



Kiwi Dataset

Algorithm	Time	Accuracy
K-Means	9.5964	64.14%
H2NMF	7.2750	58.72%
NLTV	251.1266	77.54%
APGL	220.3274	85.63%
APGL_Hyp	416.0232	86.63%

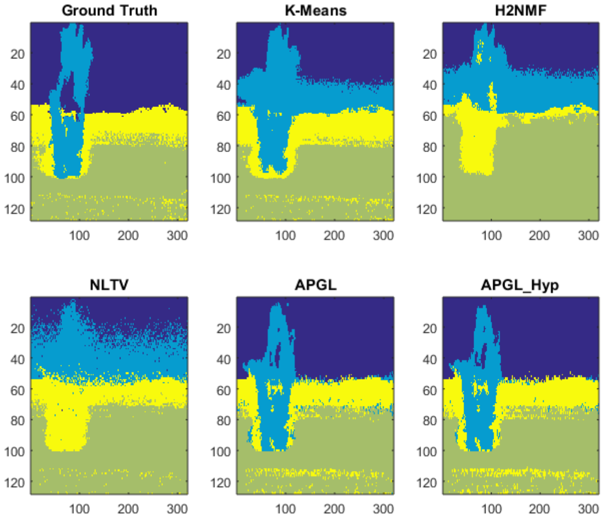
Kiwi Dataset: 10% Pixels Replaced



Kiwi Dataset: 10% Pixels Replaced

Algorithm	**Time**	**Prior Accuracy**	**Accuracy 10% Replaced**
K-Means	10.0953	64.14%	53.07%
H2NMF	8.0856	58.72%	45.14%
NLTV	279.1046	77.54%	52.24%
APGL	206.0447	85.63%	79.78%
APGL_Hyp	572.2304	86.63%	79.30%

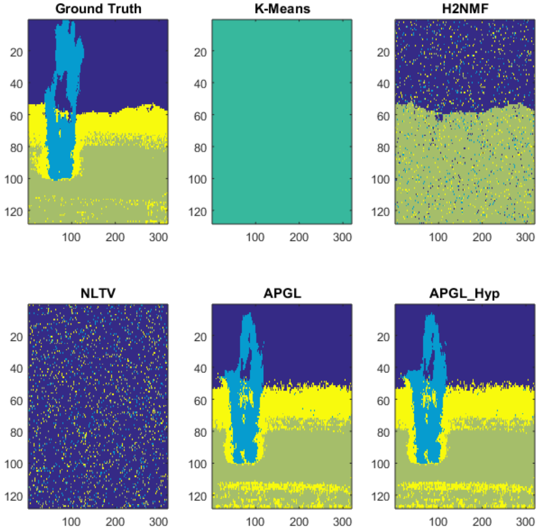
Chemical Plume Dataset



Chemical Plume Dataset

Algorithm	Time	Accuracy
K-Means	2.4594	81.44%
H2NMF	1.9909	63.42%
NLTV	92.4825	66.21%
APGL	27.6438	87.44%
APGL_Hyp	49.1695	87.24%

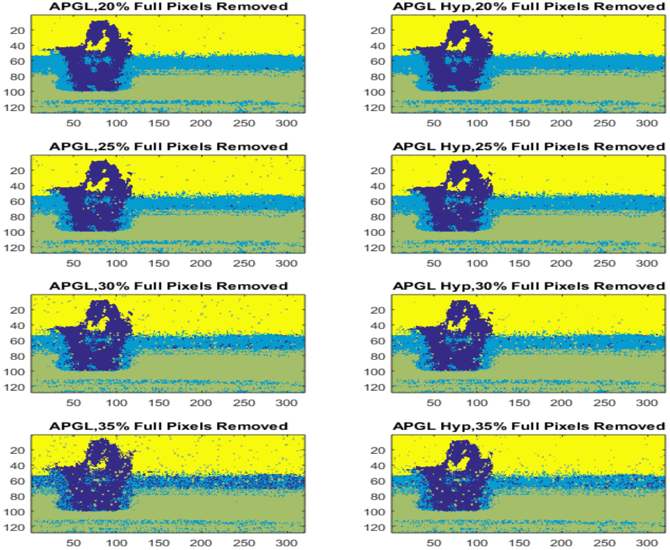
Chemical Plume Dataset: 10 % Pixels Replaced



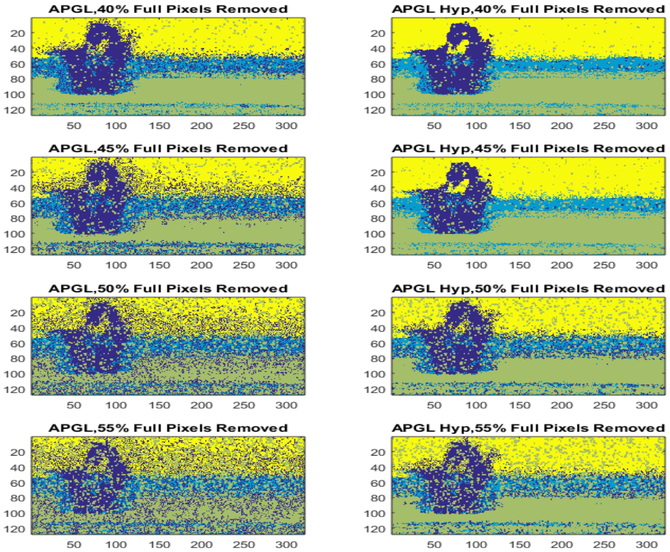
Chemical Plume Dataset: 10% Pixels Replaced

Algorithm	Time	Prior Accuracy	Accuracy 10% Replaced
K-Means	N/A	81.44%	N/A
H2NMF	2.2981	63.42%	36.23%
NLTV	99.6240	66.21%	66.53%
APGL	44.1697	87.44%	85.43%
APGL_Hyp	49.1466	87.24%	85.29%

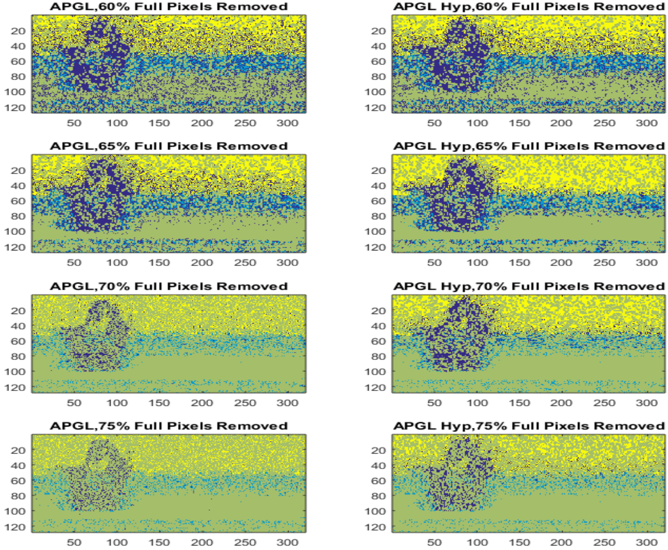
Full Pixel Removal



Full Pixel Removal



Full Pixel Removal



Full Pixel Removal

Percent Pixel Removal	Accuracy: APGL	Accuracy: APGL_Hyp
10%	85.99%	85.83%
20%	85.31%	85.36%
30%	81.85%	83.45%
40%	71.08%	81.77%
50%	60.66%	69.80%
60%	50.66%	63.42%
70%	48.61%	51.95%
80%	43.94%	44.36%

Thank You

This work was supported by NSF grants DMS-1045536, DMS-1118971, DMS-1417674, ONR grant N00014-16-1-2119, DOE grant DE-SC0013838, and Fund for Scientific Research in Flanders (FWO, Belgium) project G037115N.