Self-Tuning Complex Systems

Data Methods for Complex Systems

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Complex Systems

dynamical system

$$\mathbf{U}_t = N(\mathbf{U}, \mathbf{U}_x, \mathbf{U}_{xx}, \cdots, x, t, \beta)$$

snap shot matrix

$$\mathbf{A}_{\beta_k} = [\mathbf{U}(t_1, x)\ \mathbf{U}(t_2, x)\ \cdots\ \mathbf{U}(t_q, x)]$$

$$\Psi_k = \{\psi_i(x, \beta_k)\}_{i=1}^{r_k}$$ low-rank dynamics (SVD)

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THE EUROPEAN PHYSICAL JOURNAL SPECIAL TOPICS

Review

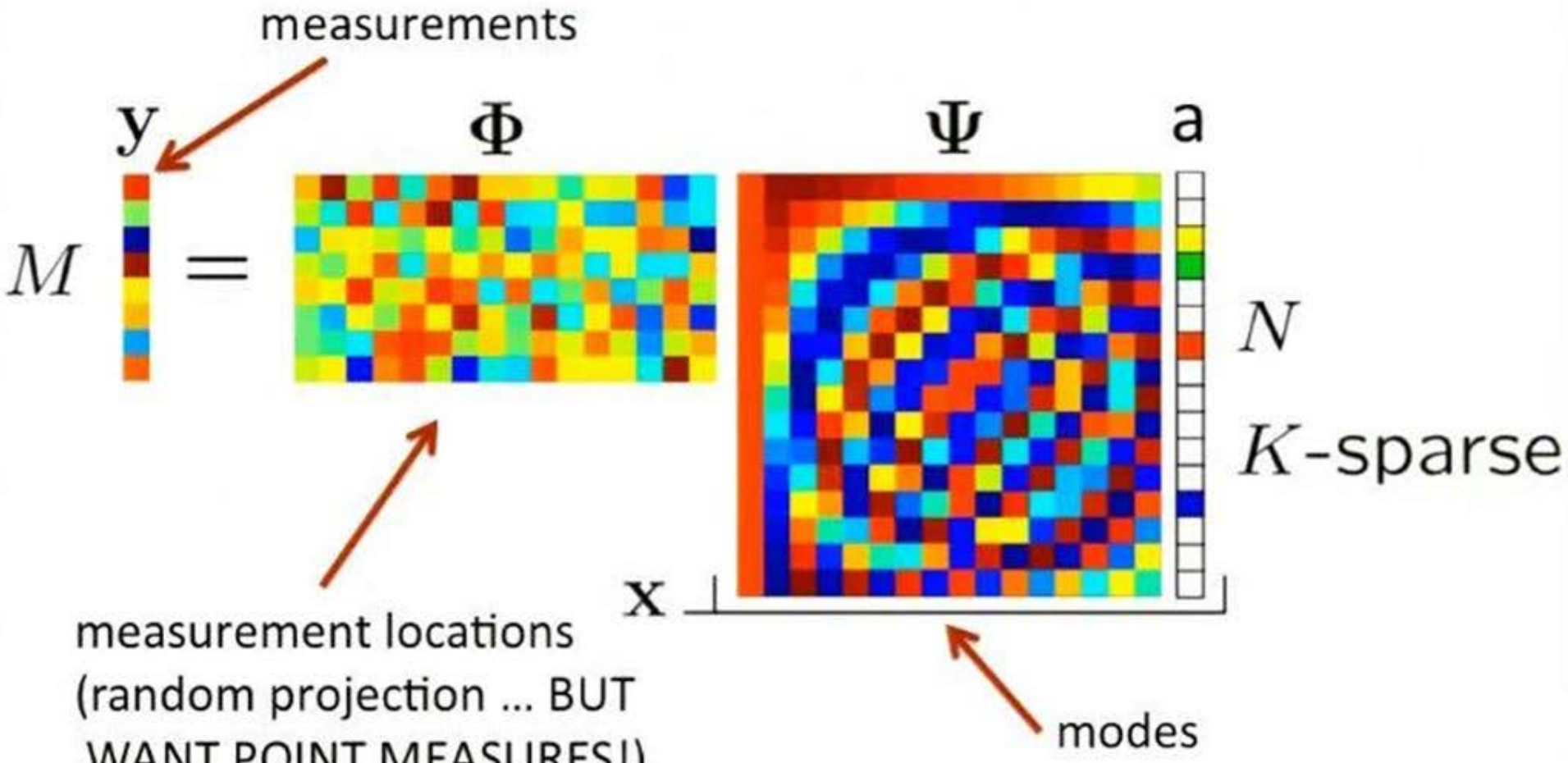
Exploiting sparsity and equation-free architectures in complex systems

SIAM J. APPLIED DYNAMICAL SYSTEMS
Vol. 13, No. 4, pp. 1719–1732

Compressive Sensing and Low-Rank Libraries for Classification of Bifurcation Regimes in Nonlinear Dynamical Systems*

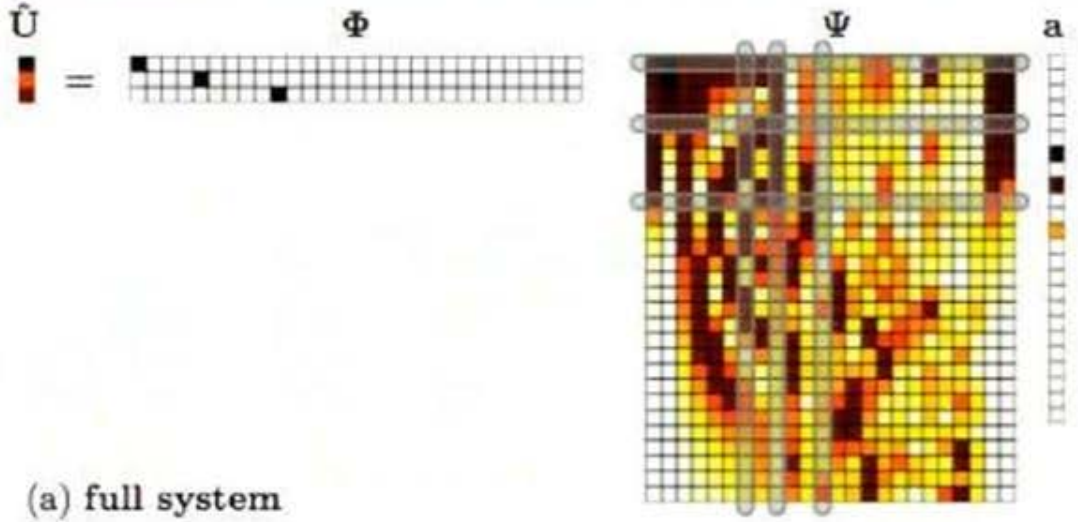
Steven L. Brunton†, Jonathan H. Tu‡, Ido Bright†, and J. Nathan Kutz‡

Compressive Sensing



R. Baraniuk, Compressive Sensing [Lecture Notes]

Measurement and Reconstruction

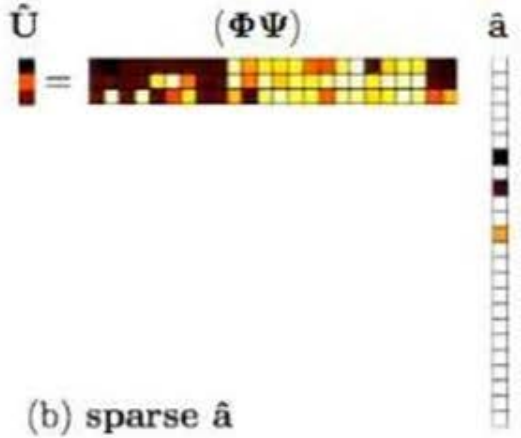


(a) full system

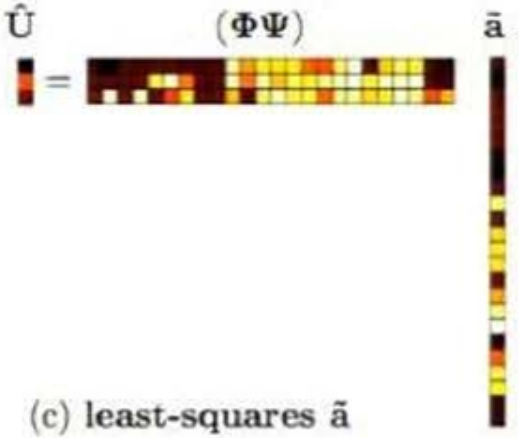
Goals

- Classification
- Reconstruction
- Future Predictions

$$\mathbf{U}(x,t) = \sum_{k=1}^{K} \sum_{m=1}^{m_k} a_{km}(t)\phi_m(x,\beta_k) = \psi_L \mathbf{a}$$



(b) sparse â

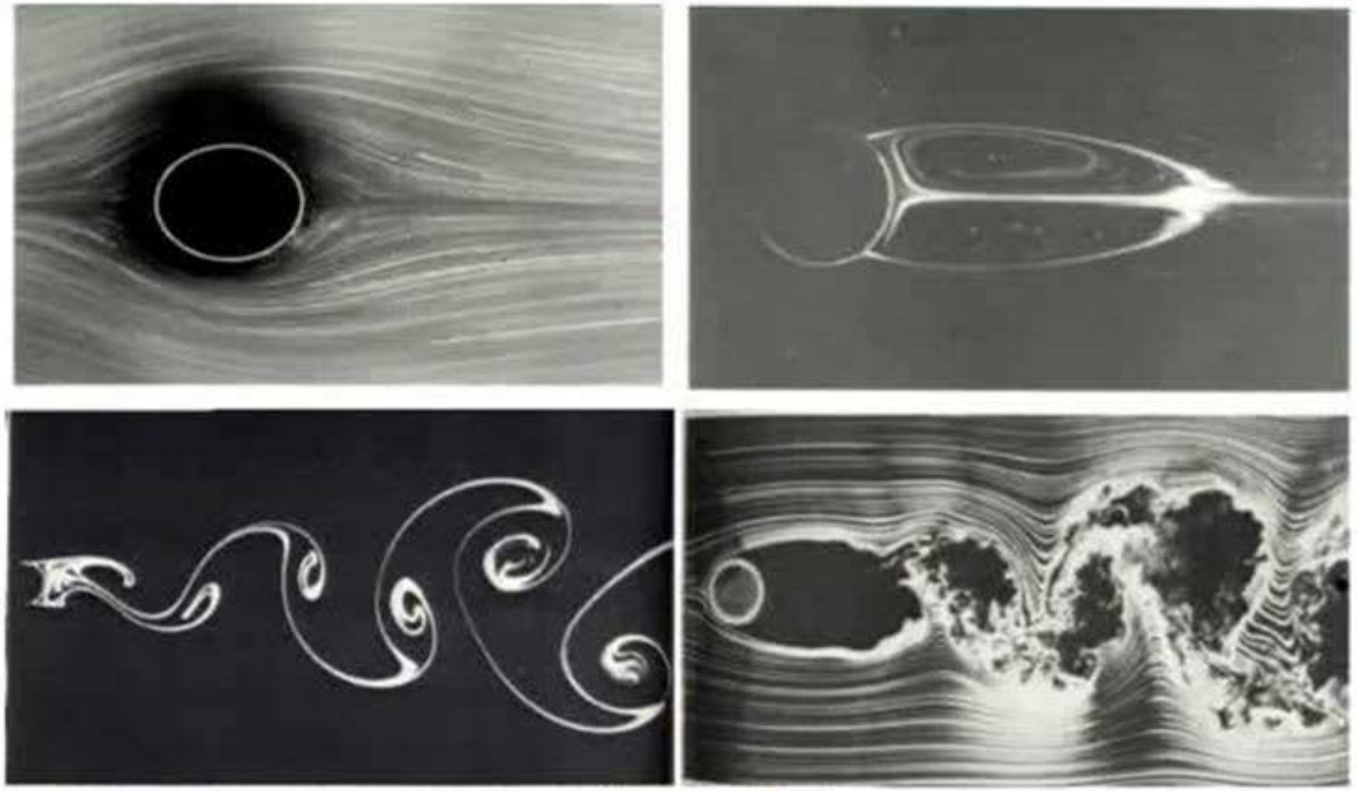


(c) least-squares ã

$$\hat{\mathbf{U}} = (\Phi\psi_L)\mathbf{a}$$

$$\min \|a\|_1$$

Compressive Sensing for PDE Dynamics



PHYSICS OF FLUIDS **25**, 127102 (2013)

Compressive sensing based machine learning strategy for characterizing the flow around a cylinder with limited pressure measurements

Ido Bright,[1] Guang Lin,[2] and J. Nathan Kutz[1,a)]

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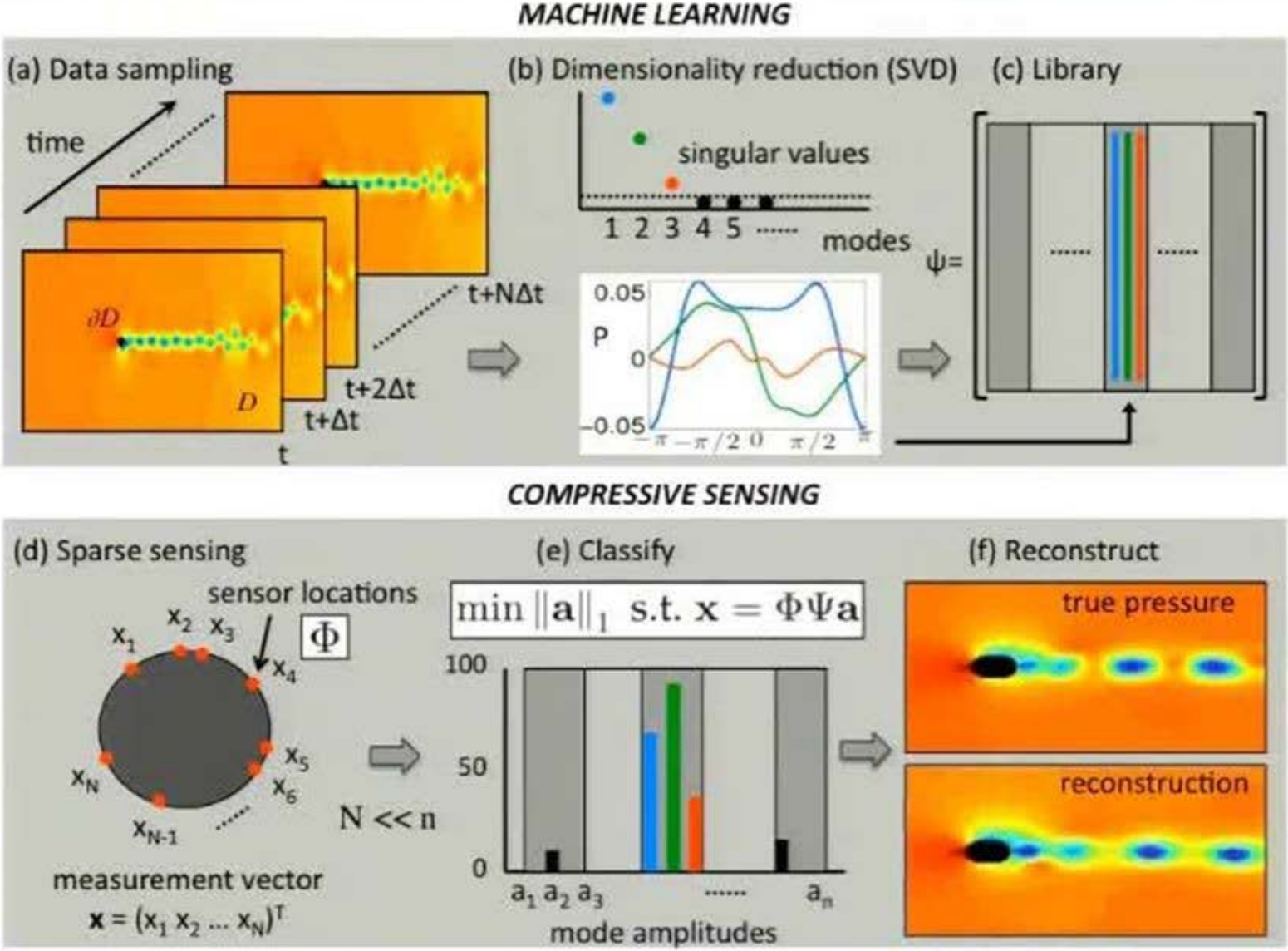
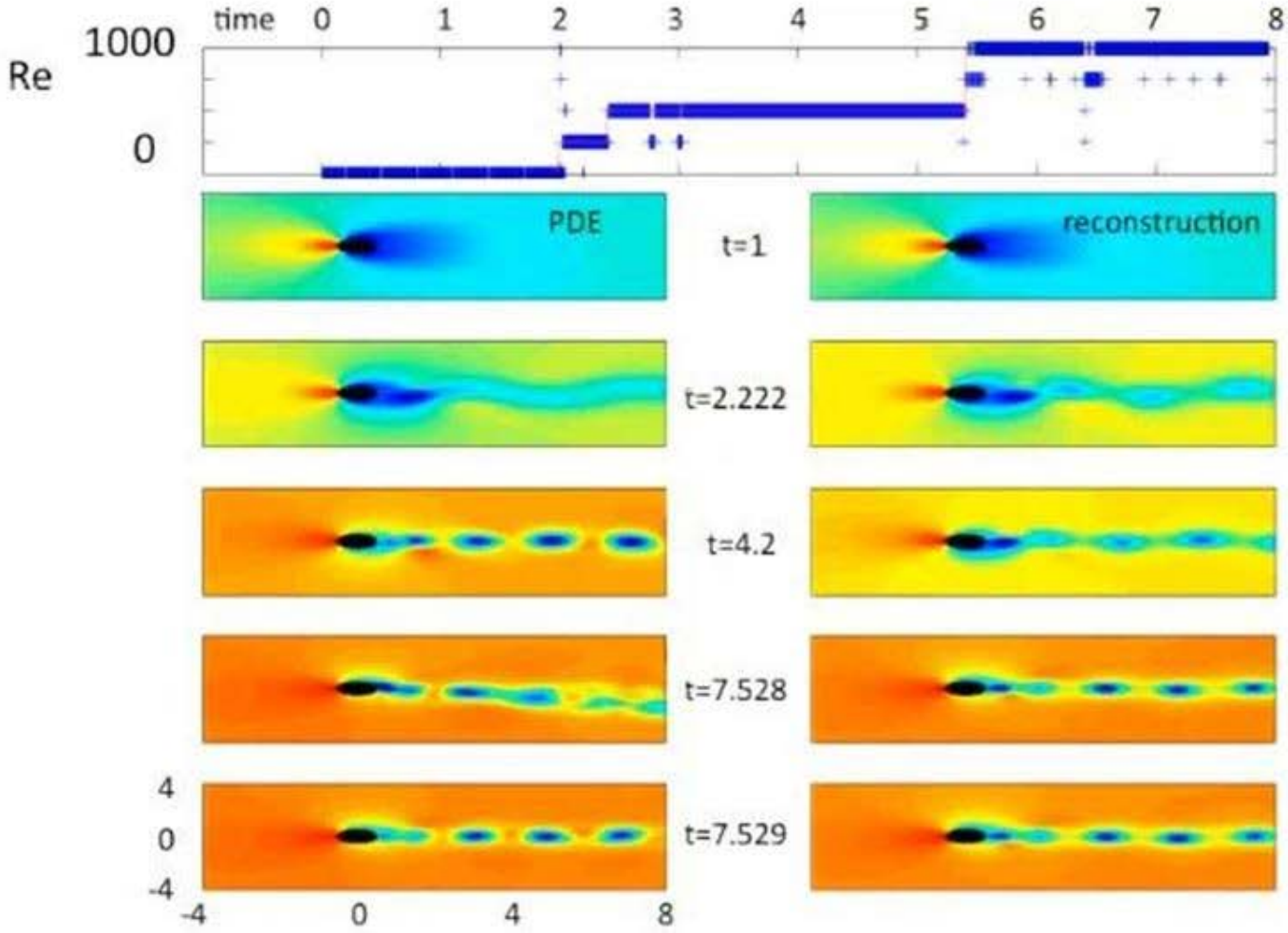
[2] *Pacific Northwest National Laboratory, PO Box 999, Richland, Washington 99352, USA*

Flow Around a Cylinder

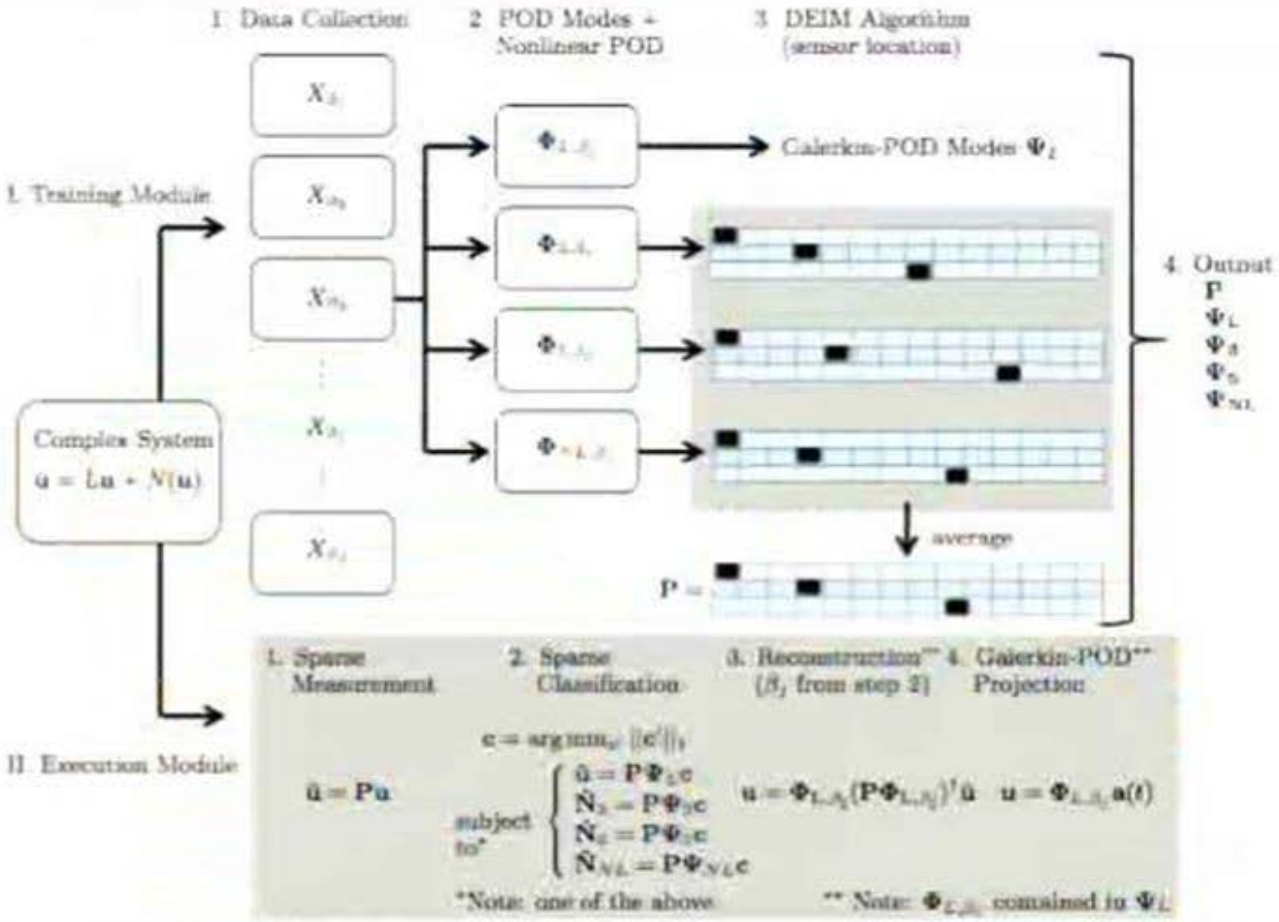


Compressive Sensing Reconstruction



What about sensor placement?

Optimizing Sensor Locations



Nonlinear Model Reduction for Complex Systems using Sparse Optimal Sensor Locations from Learned Nonlinear Libraries

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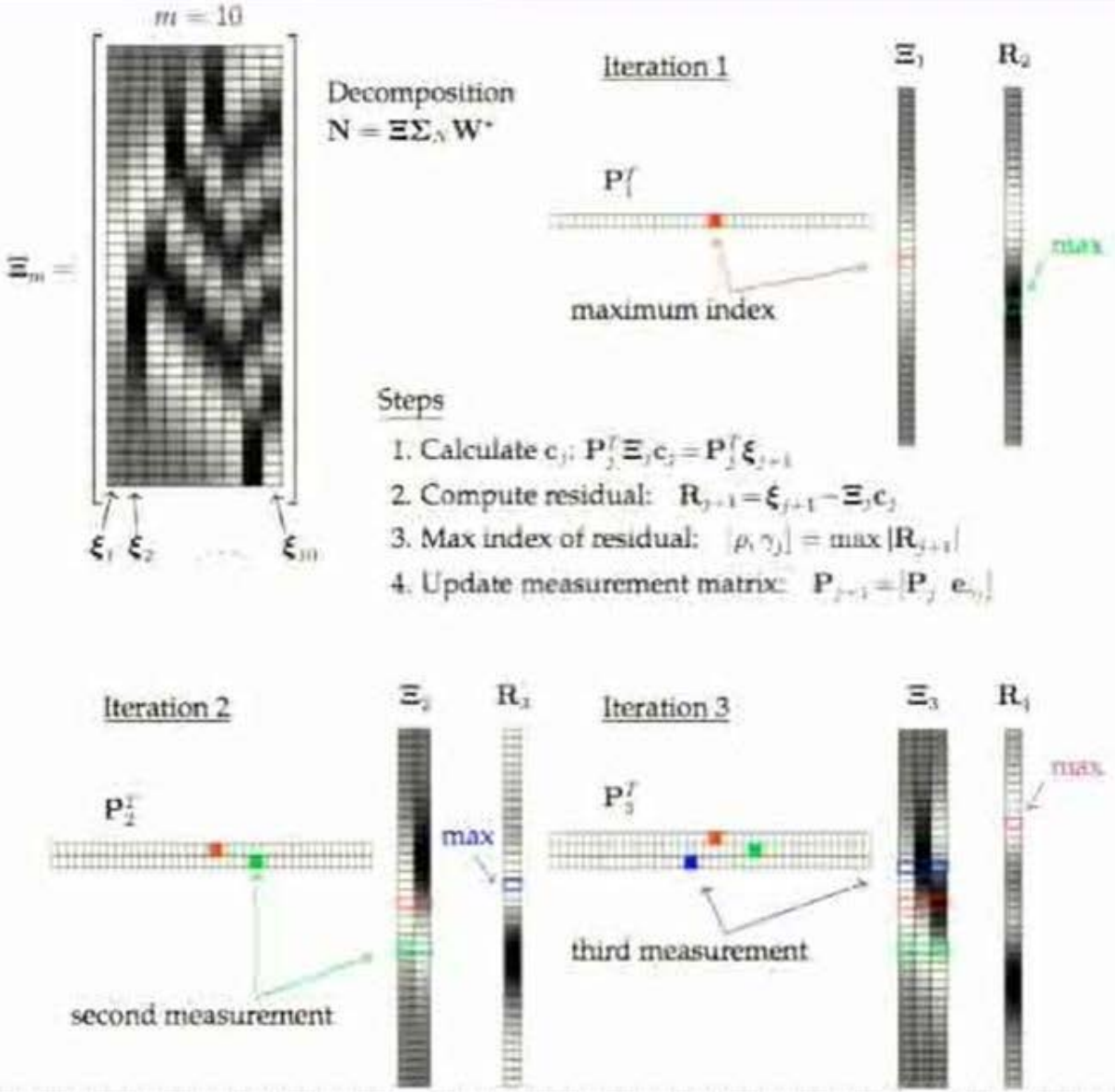
†Department of Mechanical Engineering, University of Washington, Seattle, WA 98195

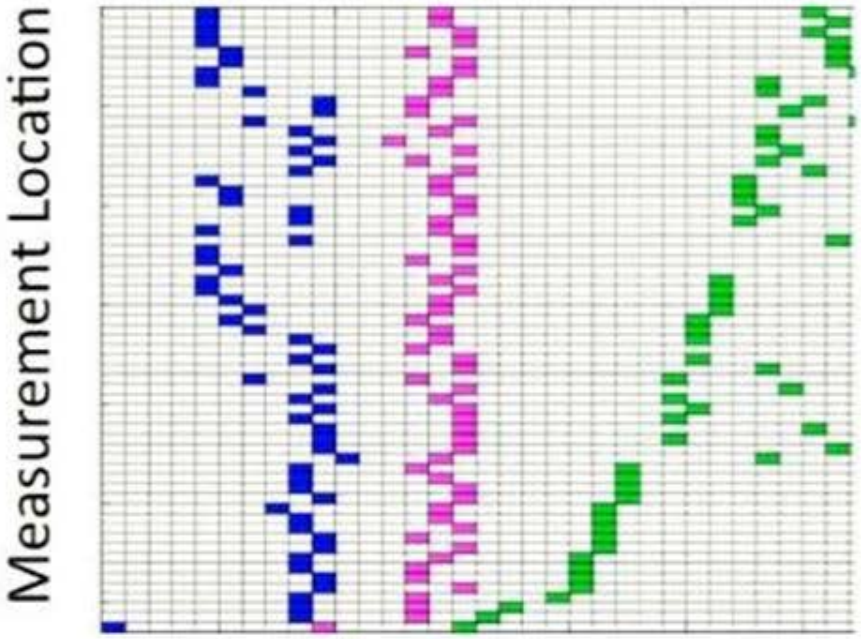
[Dated: January 19, 2015]

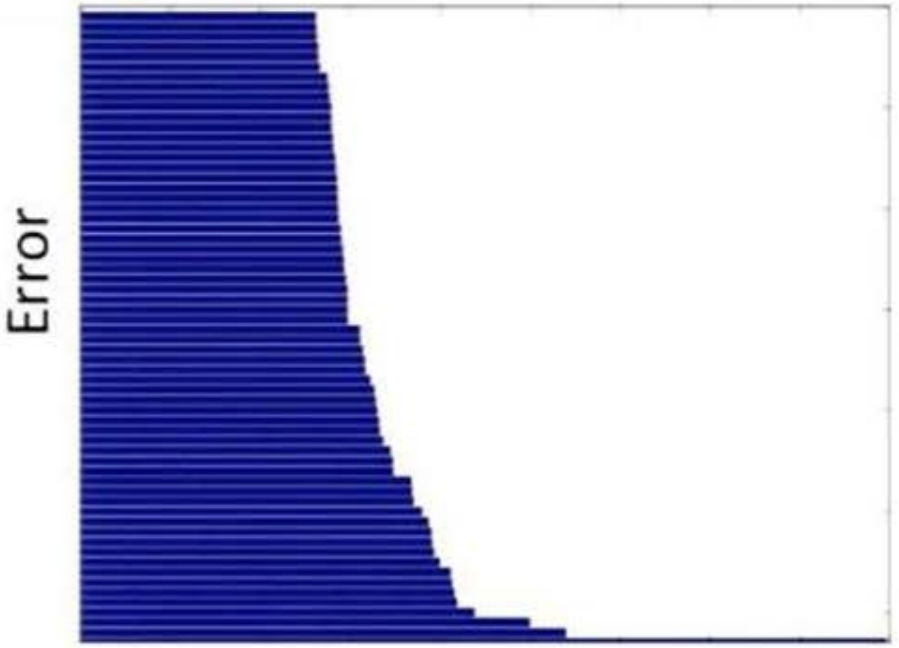
DEIM Algorithm

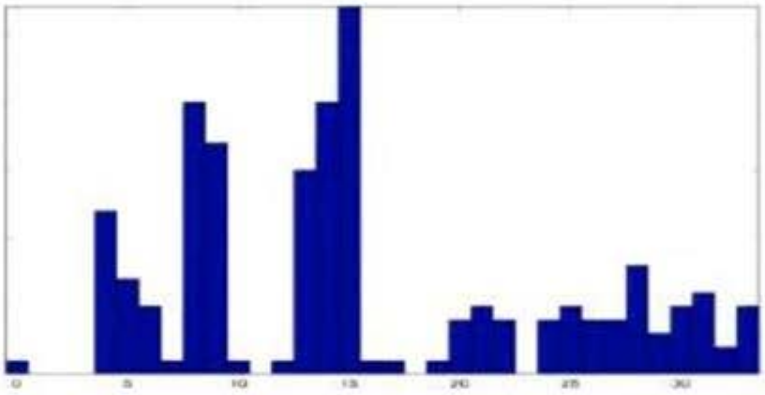


S. Chaturantabut, D. Sorensen, "Nonlinear Model Reduction via Discrete Empirical Interpolation," SIAM J. SCI. COMPUT. **32**, 2737-2764 (2010).

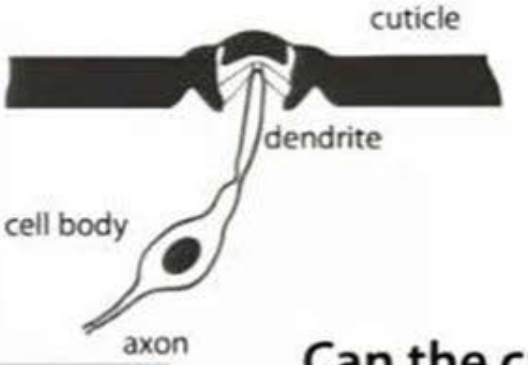
Optimal Sensors in CQGLE

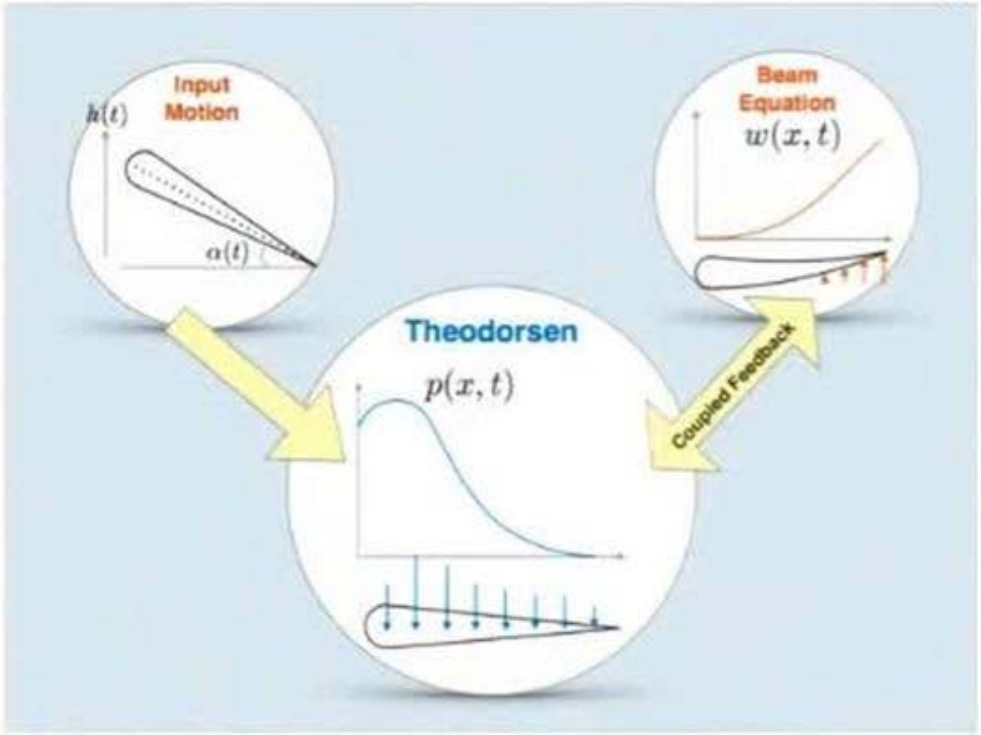






Encoding Flight - Capaniform Sensilla



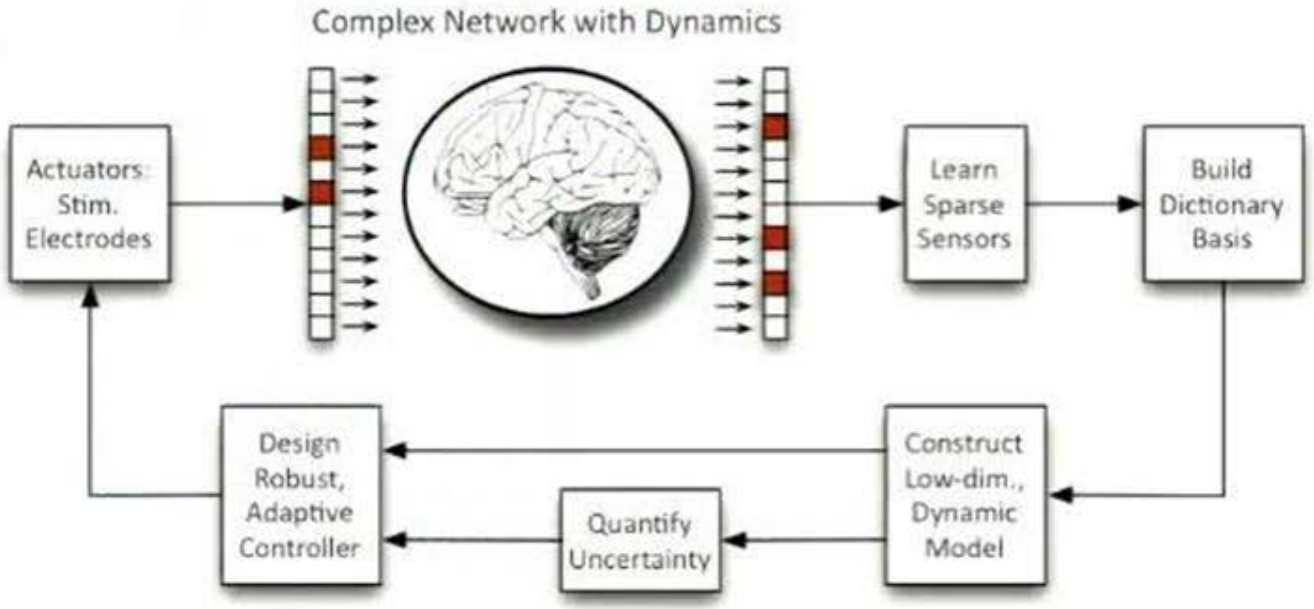


Can the campaniform sensilla on insect wings encode body dynamics or wing loading?

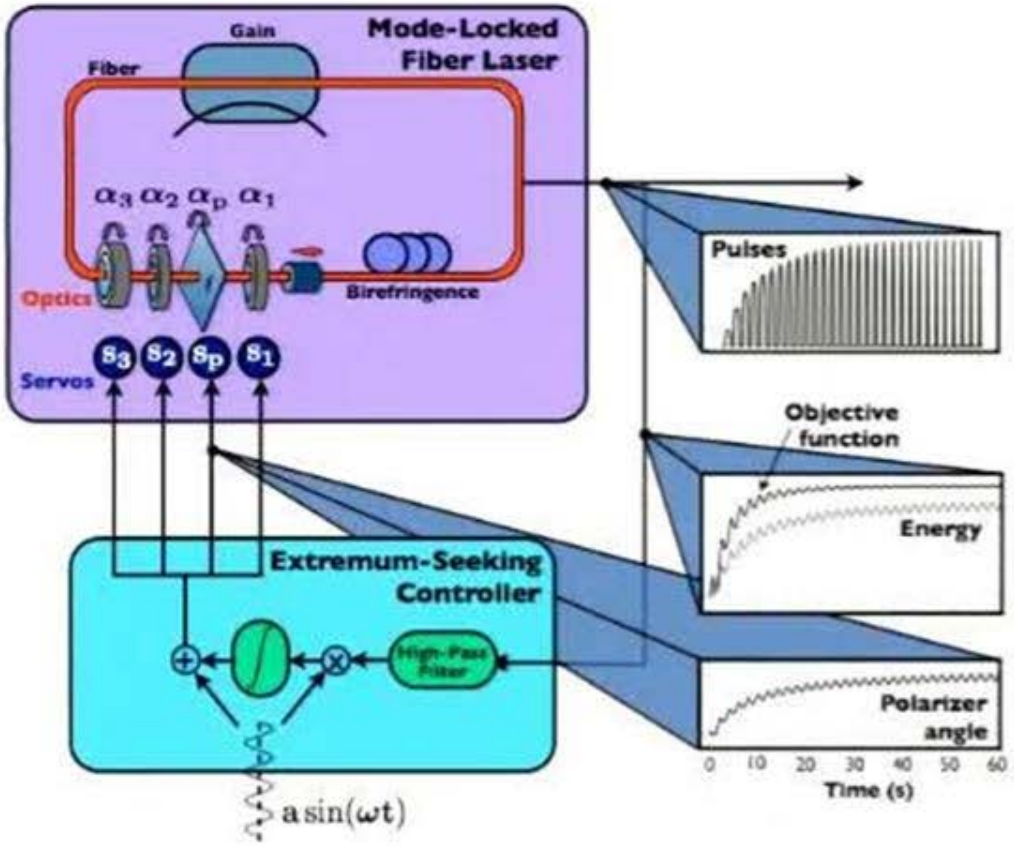
Krithika Manohar + Steve Brunton

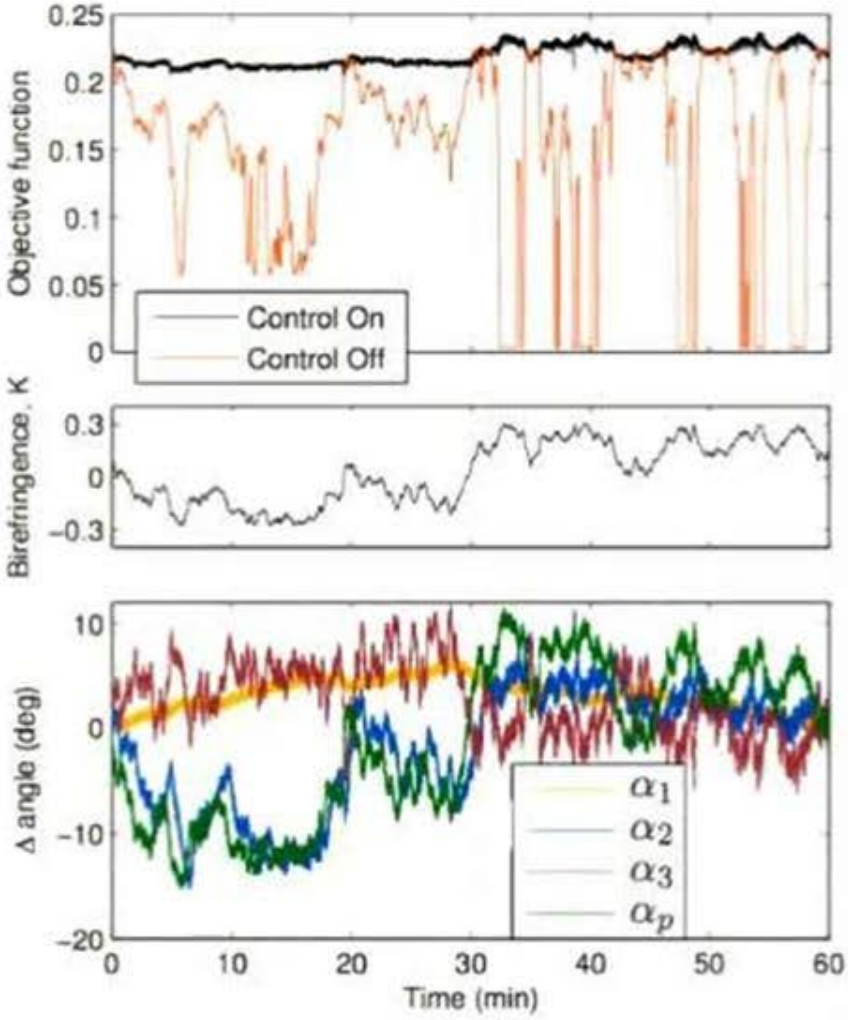
Bringing It All Together

Dynamical Systems (Equation-Free)
+ Machine Learning (robust PCA: L+M+S)
+ Compressive Sensing (time + space)
+ Control



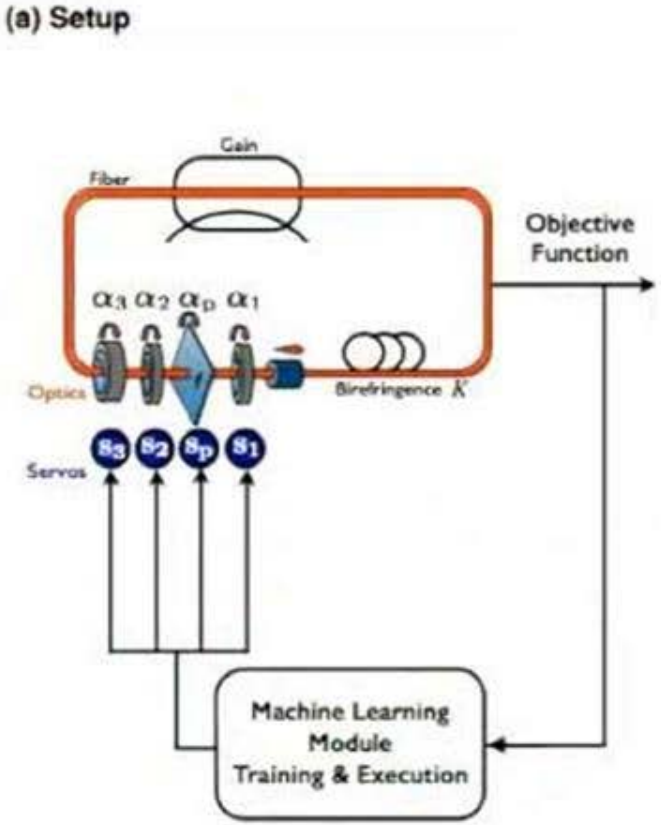
Self-Tuning Lasers

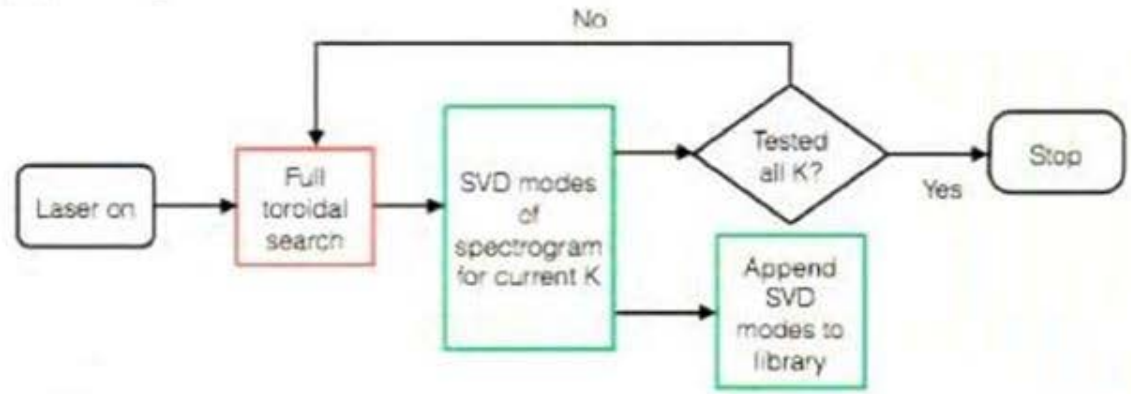


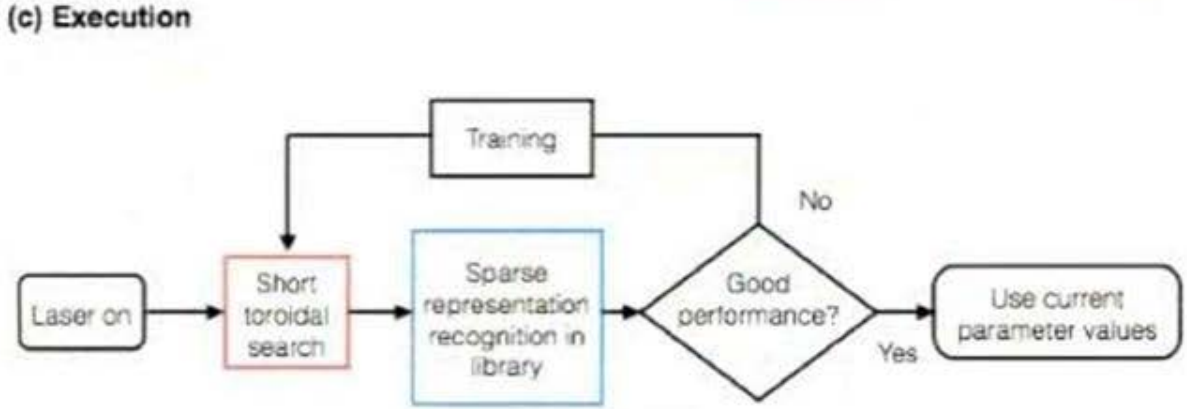


Brunton, Fu and Kutz, IEEE JSTQE (2014)

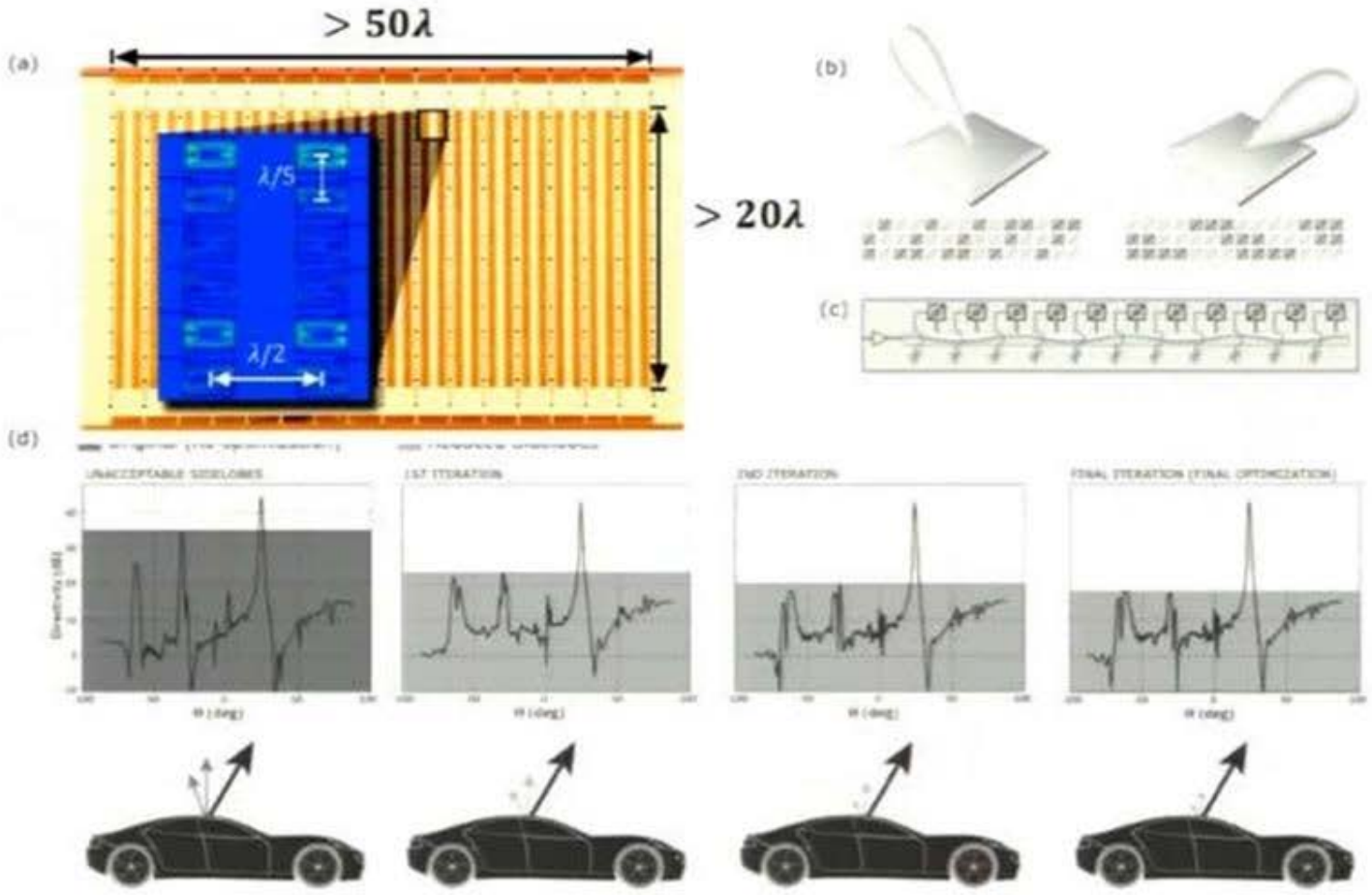
Self-Tuning Lasers





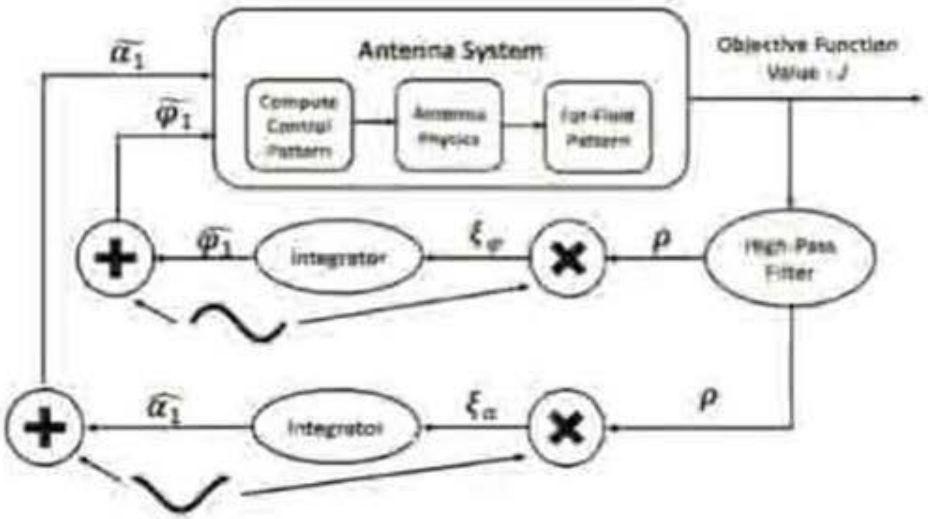


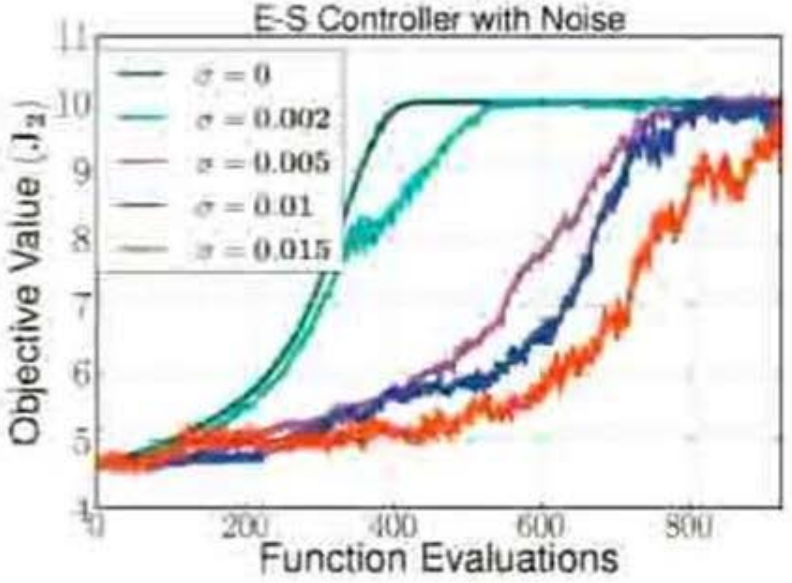
Self-tunning Metamaterial Antennas

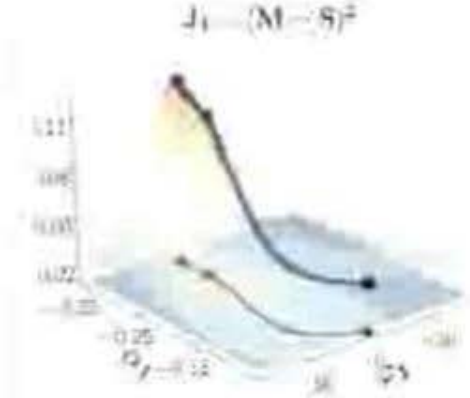


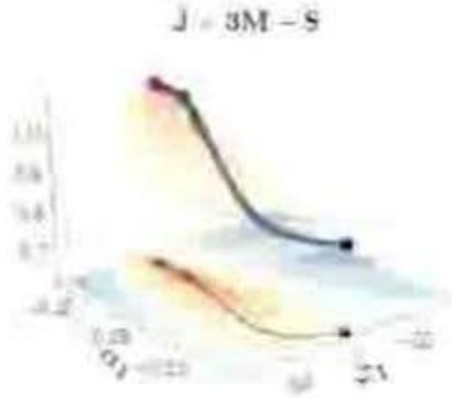
M. Johnson, S. Brunton, N. Kundtz, N. Kutz, IEEE Trans. Ant. & Prop. (2015)

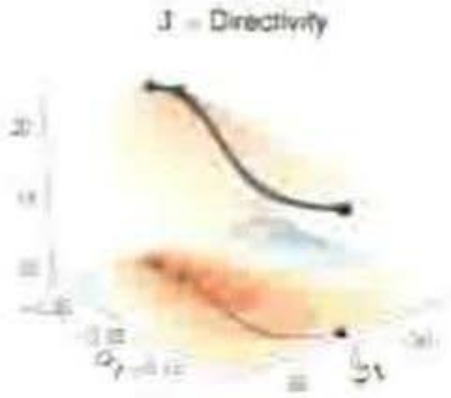
Self-tuning architecture

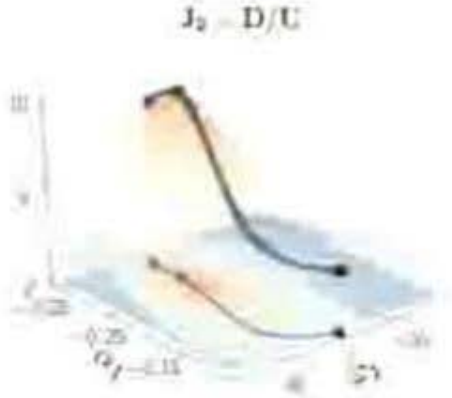












Conclusions

Dynamical Systems (Equation-Free)
+ Machine Learning (robust PCA: L+M+S)
+ Compressive Sensing (time + space)
+ Control
= Transformative Paradigm