The Dynamic Mode Decomposition: Extensions and Variations



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Dynamic Mode Decomposition

• Represent field of interest as a linear combination of DMD modes



Optimal Amplitudes

• Least-squares problem for optimal amplitudes $D_a := \operatorname{diag} \{a\}$





Chen, Tu, Rowley, J. Nonlinear Sci. '12

• AN EXAMPLE

***** unstructured LES of a screeching supersonic jet



• CHALLENGE

*** desirable tradeoff between**

quality of approximation number of DMD modes



Outline

- **1** Sparsity-promoting DMD
 - ***** Performance vs sparsity
 - ***** Tools from optimization and compressive sensing

- **A**LGORITHM
 - ***** Alternating direction method of multipliers

- **3** AN EXAMPLE
 - ***** Screeching supersonic jet

Sparsity-promoting DMD



 \star card (a) – number of non-zero elements

$$a := \begin{bmatrix} 1.4 & \mathbf{0} & \mathbf{0} & -8.1 & \mathbf{0} \end{bmatrix}^T \Rightarrow \operatorname{card}(a) = 2$$

 $\star \gamma > 0$ – performance vs sparsity tradeoff

Convex Relaxation of card(a)



Convex Optimization Problem

• Step 1: structure-identification



• Step 2: polishing

minimize J(a)subject to E a = 0

• Outcome: parameterized family of optimal amplitudes



An example: Screeching Supersonic Jet



- UNSTRUCTURED LES OF A RECTANGULAR JET
 - * Aspect ratio 4:1; Mach 1.4
 - ★ 45M control volumes (CharLES)

• PRESSURE AT TWO LOCATIONS



Performance vs Sparsity



least-squares approximation:

sparsity-promoting parameter

sparsity-promoting parameter

number of non-zero amplitudes:

• SPECTRUM



• AMPLITUDE VS FREQUENCY



• AMPLITUDE VS FREQUENCY



• AMPLITUDE VS FREQUENCY



Algorithm: Alternating Direction Method of Multipliers

minimize
$$J(a) + \gamma g(a)$$

• Step 1: introduce additional variable/constraint

minimize $J(a) + \gamma g(b)$ subject to a - b = 0

benefit: decouples J and g

• Step 2: introduce augmented Lagrangian

$$\mathcal{L}_{\rho}(a,b,\lambda) := J(a) + \gamma g(b) + \langle \lambda, a - b \rangle + \frac{\rho}{2} \|a - b\|_2^2$$

• Step 3: use ADMM for augmented Lagrangian minimization

$$\mathcal{L}_{\rho}(a,b,\lambda) = J(a) + \gamma g(b) + \langle \lambda, a - b \rangle + \frac{\rho}{2} \|a - b\|_{2}^{2}$$

ADMM:

$$a^{k+1} := \arg\min_{a} \mathcal{L}_{\rho}(a, b^{k}, \lambda^{k})$$
$$b^{k+1} := \arg\min_{b} \mathcal{L}_{\rho}(a^{k+1}, \mathbf{b}, \lambda^{k})$$
$$\lambda^{k+1} := \lambda^{k} + \rho \left(a^{k+1} - b^{k+1}\right)$$

Step 4: Polishing – structured optimal design

***** ADMM: tool for identifying sparsity patterns

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REFERENCE

Jovanović, Schmid, Nichols, CTR Annual Research Briefs 2012