# Hamiltonian and Symplectic Lanczos Processes

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# **Problem: Linear Elasticity**

• 
$$(\lambda^2 M + \lambda G + K)v = 0$$
  
 $M^T = M > 0$   $G^T = -G$   $K^T = K < 0$ 

- quadratic eigenvalue problem
- large, sparse (finite elements)
- Find few eigenvalues nearest imaginary axis (and corresponding eigenvectors).

# **Problem: Optimal Control**

$$\bullet \begin{bmatrix} A & BB^T \\ C^TC & -A^T \end{bmatrix} - \lambda \begin{bmatrix} E & 0 \\ 0 & E^T \end{bmatrix}$$
 (large and sparse)

Hamiltonian/skew-Hamiltonian

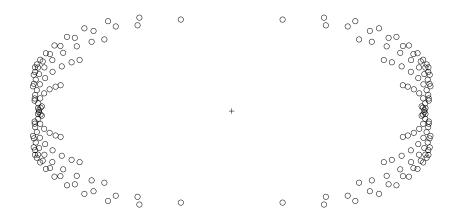
• multiply by 
$$J = \left[ \begin{array}{cc} \mathbf{0} & I \\ -I & \mathbf{0} \end{array} \right]$$

$$\bullet \left[ \begin{array}{cc} C^T C & -A^T \\ -A & -BB^T \end{array} \right] - \lambda \left[ \begin{array}{cc} \mathsf{0} & E^T \\ -E & \mathsf{0} \end{array} \right]$$

symmetric/skew-symmetric

#### **Hamiltonian Structure**

- Our matrices are real.
- $\lambda$ ,  $\overline{\lambda}$ ,  $-\overline{\lambda}$ ,  $-\lambda$  occur together.
- seen also in Hamiltonian matrices



#### **Hamiltonian Matrices**

• 
$$H \in \mathbb{R}^{2n \times 2n}$$

$$\bullet \ J = \begin{bmatrix} 0 & I \\ -I & 0 \end{bmatrix} \in \mathbb{R}^{2n \times 2n}$$

ullet H is Hamiltonian iff JH is symmetric.

$$\bullet \ \ H = \left[ \begin{array}{cc} A & K \\ N & -A^T \end{array} \right],$$
 where  $K = K^T$  and  $N = N^T$ 

#### Linearization

• 
$$\lambda^2 Mv + \lambda Gv + Kv = 0$$

• 
$$w = \lambda v$$
,  $Mw = \lambda Mv$ 

$$\bullet \left[ \begin{array}{cc} -K & \mathbf{0} \\ \mathbf{0} & -M \end{array} \right] \left[ \begin{array}{c} v \\ w \end{array} \right] - \lambda \left[ \begin{array}{cc} G & M \\ -M & \mathbf{0} \end{array} \right] \left[ \begin{array}{c} v \\ w \end{array} \right] = \mathbf{0}$$

• 
$$Ax - \lambda Nx = 0$$

• symmetric/skew-symmetric

#### **Reduction to Hamiltonian Matrix**

•  $A - \lambda N$  (symmetric/skew-symmetric)

• 
$$N = R^T J R$$
  $\left(J = \begin{bmatrix} 0 & I \\ -I & 0 \end{bmatrix}\right)$  sometimes easy, always possible

• Transform:

$$A - \lambda R^T J R$$

$$R^{-T}AR^{-1} - \lambda J$$

$$J^T R^{-T} A R^{-1} - \lambda I$$

•  $H = J^T R^{-T} A R^{-1}$  is Hamiltonian.

## **Example**

$$\bullet \ \ N = \left[ \begin{array}{cc} G & M \\ -M & 0 \end{array} \right]$$

• 
$$N = R^T J R = \begin{bmatrix} I & -\frac{1}{2}G \\ 0 & M \end{bmatrix} \begin{bmatrix} 0 & I \\ -I & 0 \end{bmatrix} \begin{bmatrix} I & 0 \\ \frac{1}{2}G & M \end{bmatrix}$$

•

$$H = J^{T}R^{-T}AR^{-1}$$

$$= \begin{bmatrix} I & 0 \\ -\frac{1}{2}G & I \end{bmatrix} \begin{bmatrix} 0 & M^{-1} \\ -K & 0 \end{bmatrix} \begin{bmatrix} I & 0 \\ -\frac{1}{2}G & I \end{bmatrix}$$

## Sparse Representation of H

- Krylov subspace methods
- We just need to apply the operator.  $(M = LL^T)$

$$H = \begin{bmatrix} I & 0 \\ -\frac{1}{2}G & I \end{bmatrix} \begin{bmatrix} 0 & M^{-1} \\ -K & 0 \end{bmatrix} \begin{bmatrix} I & 0 \\ -\frac{1}{2}G & I \end{bmatrix}$$

$$H^{-1} = \begin{bmatrix} I & 0 \\ \frac{1}{2}G & I \end{bmatrix} \begin{bmatrix} 0 & (-K)^{-1} \\ M & 0 \end{bmatrix} \begin{bmatrix} I & 0 \\ \frac{1}{2}G & I \end{bmatrix}$$

# **Exploitable Structures**

• Hamiltonian

$$H^{-1}$$

$$H^{-1}(H - \tau I)^{-1}(H + \tau I)^{-1}$$

skew-Hamiltonian

$$H^{-2}$$

$$(H - \tau I)^{-1}(H + \tau I)^{-1}$$

• symplectic

$$(H - \tau I)^{-1}(H + \tau I)$$

 $\tau = \text{target shift}$ 

Note:  $(H-\tau I)^{-1}$  has none of these structures.

# **Unsymmetric Lanczos Process**

 Standard unsymmetric Lanczos effects a (partial) similarity transformation

$$A \left[ u_1 \cdots u_n \right] = \left[ u_1 \cdots u_n \right]$$

$$U^{-1}AU = \left[\begin{array}{c} \\ \\ \end{array}\right]$$

• partial similarity transformation:

$$A \begin{bmatrix} u_1 & \cdots & u_k \end{bmatrix} = \begin{bmatrix} u_1 & \cdots & u_k \end{bmatrix} \begin{bmatrix} & & \\ & & \end{bmatrix} + u_{k+1} \beta_k e_k^T$$

short Lanczos runs (breakdowns!!, no look-ahead)

$$A \begin{bmatrix} u_1 & \cdots & u_k \end{bmatrix} = \begin{bmatrix} u_1 & \cdots & u_k \end{bmatrix} \begin{bmatrix} & & \\ & & \end{bmatrix} + u_{k+1} \beta_k e_k^T$$

- Get eigenvalues of [ ]
- Restart (implicitly)

IRA (Sorensen 1991), ARPACK

Restart Lanczos with HR (Grimme/Sorensen/Van Dooren 1996)

#### **Structured Lanczos Methods**

- Similarity transformation:  $S^{-1}AS = \hat{A}$
- S symplectic  $\Rightarrow$  structure preserved
  - symplectic (Lie group)
  - Hamiltonian (Lie algebra)
  - skew-Hamiltonian (Jordan algebra)
- Conclusion: A "Lanczos" process that builds a symplectic similarity transformation will preserve structure.

Vectors produced should be columns of a symplectic matrix.

# **Symplectic Matrices**

• 
$$S \in \mathbb{R}^{2n \times 2n}$$

$$\bullet \ S^T J S = J \qquad \left( J = \begin{bmatrix} 0 & I \\ -I & 0 \end{bmatrix} \right)$$

$$\bullet$$
  $S = \left[ \begin{array}{cc} U & V \end{array} \right]$ 

$$\bullet \ \left[ \begin{array}{c} U^T \\ V^T \end{array} \right] J \left[ \begin{array}{cc} U & V \end{array} \right] = \left[ \begin{array}{cc} \mathsf{0} & I \\ -I & \mathsf{0} \end{array} \right]$$

• 
$$U^TJU = 0$$
,  $V^TJV = 0$ ,  $U^TJV = I$ 

• Subspaces are isotropic.

# **Isotropic Subspaces**

• 
$$y^TJx = 0$$
 for all  $x, y \in \mathcal{U}$ 

$$\bullet$$
  $U = \begin{bmatrix} u_1 & \cdots & u_k \end{bmatrix}$ 

• 
$$U^TJU = 0$$

• Structured methods build isotropic subspaces.

#### **Skew-Hamiltonian Case**

**Theorem:** B skew Hamiltonian,  $x \neq 0 \Rightarrow$ 

 $\operatorname{span}\{x, Bx, \dots, B^{j-1}x\}$  is isotropic.

- Conclusion: Krylov subspace methods preserve skew-Hamiltonian structure automatically.
- Examples: Arnoldi, unsymmetric Lanczos
- exact vs. floating-point arithmetic

#### Skew-Hamiltonian Arnoldi Process

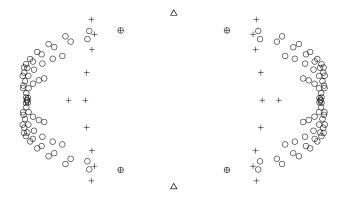
• Isotropic Arnoldi process

$$\tilde{q}_{j+1} = Bq_j - \sum_{i=1}^{j} q_i h_{ij} - \sum_{i=1}^{j} Jq_i t_{ij}$$

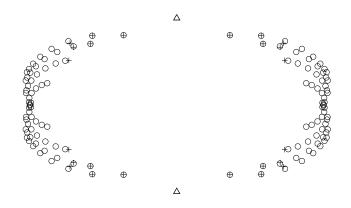
- produces *isotropic* subspaces:  $Jq_1, \ldots, Jq_k$  are orthogonal to  $q_1, \ldots, q_k$ .
- Theory  $t_{ij} = 0$
- Practice  $t_{ij} = \epsilon$  (roundoff)
- Enforcement of isotropy is crucial.
- Consequence: get each eigenvalue only once.

## **Example**

- Method: Implicitly Restarted Arnoldi (effective combination of Arnoldi and subspace iteration)
- Toy problem (n = 64); asking for 8 eigenvalues (right half-plane).
- Target  $\tau = i$  (not particularly good)
- After 12 Arnoldi steps (no restart) ...



After one restart (12 more Arnoldi steps)



- Errors:  $10^{-14}$ ,  $10^{-7}$ ,  $10^{-6}$ ,  $10^{-2}$
- After 7 iterations (restarts) algorithm stops with 8 eigenvalues correct to ten decimal places.
- Residuals:  $\|(\lambda^2 M + \lambda G + K)v\| \le 10^{-12}$  ( $\|v\| = 1$ )

# **Further Experience**

- Fortran/C code
- $n \approx 2 \times 10^5$
- Disadvantage: Eigenvectors cost extra. (eigenvectors of  $H^2$  vs. H)
- We haven't done skew-Hamiltonian Lanczos.

#### **Hamiltonian Case**

• Bunse-Gerstner/Mehrmann 1986:

$$S^{-1}HS = \left[ \begin{array}{cc} E & T \\ D & -E \end{array} \right] = \left[ \begin{array}{cc} & & \\ & & \\ & & \end{array} \right]$$

- Further condensation: E = 0,  $D = \text{diag}\{\pm 1 \cdots \pm 1\}$ .
- $\bullet$   $S = \left[ \begin{array}{cc} U & V \end{array} \right]$
- $\bullet \ H \left[ \begin{array}{cc} U & V \end{array} \right] = \left[ \begin{array}{cc} U & V \end{array} \right] \left[ \begin{array}{cc} \mathsf{0} & T \\ D & \mathsf{0} \end{array} \right]$

#### Condensed

#### **Hamiltonian Lanczos Process**

• 
$$H \begin{bmatrix} U & V \end{bmatrix} = \begin{bmatrix} U & V \end{bmatrix} \begin{bmatrix} & & & \\ & & & \end{bmatrix}$$

$$U = \begin{bmatrix} u_1 & u_2 & \cdots \end{bmatrix} \quad V = \begin{bmatrix} v_1 & v_2 & \cdots \end{bmatrix}$$

- $Hu_k = v_k d_k$  $Hv_k = u_{k-1}b_{k-1} + u_k a_k + u_{k+1}b_k$
- $u_{k+1}b_k = Hv_k u_k a_k u_{k-1}b_{k-1}$  $v_{k+1}d_{k+1} = Hu_{k+1}$
- Coefficients are chosen so that  $S = \begin{bmatrix} U & V \end{bmatrix}$  is symplectic.
- Collect coefficients.

### **Equivalence**

- $H^2$  is skew-Hamiltonian.
- Condensed Hamiltonian Lanczos applied to H is theoretically equivalent to ordinary Lanczos applied to  $H^2$ .
- Hamiltonian algorithm costs half as many matrix-vector multiplies.

# **Isotropy**

$$\bullet \ S^T J S = J, \quad J = \begin{bmatrix} 0 & I \\ -I & 0 \end{bmatrix}$$

$$\bullet \left[ \begin{array}{c} U^T \\ V^T \end{array} \right] J \left[ \begin{array}{cc} U & V \end{array} \right] = \left[ \begin{array}{cc} \mathsf{0} & I \\ -I & \mathsf{0} \end{array} \right]$$

- $U^TJU = 0$ , (isotropic subspaces)  $V^TJV = 0$ ,
- In (floating-point) practice, isotropy must be enforced by J-reorthogonalization.
- All vectors must be retained.
- short Lanczos runs, restarts

# Implicitly Restarted Hamiltonian Lanczos Process

- use SR, not QR (Benner/Fassbender 1997)
- In condensed case, SR = HR (Benner/Fassbender/W 1998)
- ullet Use of HR yields significant simplification.

# **Symplectic Case**

#### **Structure**

- Eigenvalues of S appear in quartets  $\mu$ ,  $\mu^{-1}$ ,  $\overline{\mu}$ ,  $\overline{\mu}^{-1}$ .
- Symplectic Lanczos process must extract these simultaneously.
- This is accomplished by using both S and  $S^{-1}$ .
- $S^{-1} = -JS^TJ$

# Symplectic Similarity

symplectic butterfly form:
 (Banse/Bunse-Gerstner 1994)

$$W^{-1}SW = \begin{bmatrix} D_1 & T_1 \\ D_2 & T_2 \end{bmatrix} = \begin{bmatrix} \boxed{\phantom{a}} \\ \boxed{\phantom{a}} \end{bmatrix}$$

- Further condensation:  $D_1 = 0$ ,  $D_2 = \text{diag}\{\pm 1 \cdots \pm 1\}$ ,  $T_1 = -D_2$ , ...
- $\bullet \ W = \left[ \begin{array}{cc} U & V \end{array} \right]$
- $\bullet \ S \left[ \begin{array}{cc} U & V \end{array} \right] = \left[ \begin{array}{cc} U & V \end{array} \right] \left[ \begin{array}{cc} \mathsf{0} & -D \\ D & DT \end{array} \right]$

# Condensed Symplectic Lanczos Process

$$\bullet \ S \left[ \ U \ \ V \ \right] = \left[ \ U \ \ V \ \right]$$

- $Su_k = v_k d_k$  $Sv_k = -u_k d_k + v_{k-1} \tilde{b}_{k-1} + v_k \tilde{a}_k + v_{k+1} \tilde{b}_k$
- $v_{k+1}\tilde{b}_k = Sv_k v_k\tilde{a}_k v_{k-1}\tilde{b}_{k-1} + u_kd_k$  $u_{k+1}d_{k+1} = S^{-1}v_{k+1}$
- ullet Coefficients are chosen so that  $\left[egin{array}{cc} U & V \end{array}
  ight]$  is symplectic.
- Collect coefficients.

## **Equivalence**

- $S + S^{-1}$  is skew-Hamiltonian.
- Condensed symplectic Lanczos applied to S is theoretically equivalent to ordinary Lanczos applied to  $S+S^{-1}$ .
- Symplectic algorithm costs half as many matrix-vector multiplies.

# **Isotropy** (rerun)

$$\bullet \left[ \begin{array}{c} U^T \\ V^T \end{array} \right] J \left[ \begin{array}{cc} U & V \end{array} \right] = \left[ \begin{array}{cc} \mathsf{0} & I \\ -I & \mathsf{0} \end{array} \right]$$

- $U^TJU = 0$ , (isotropic subspaces)  $V^TJV = 0$ ,
- In (floating-point) practice, isotropy must be enforced by J-reorthogonalization.
- All vectors must be retained.
- short Lanczos runs, restarts

# Implicitly Restarted Symplectic Lanczos Process

- ullet use symplectic SR, not QR
- In condensed case, SR = HR (Benner/Fassbender/W 1998)
- Use of HR yields **significant** simplification.

## **Remarks on Stability**

- Both Hamiltonian and symplectic Lanczos processes are potentially unstable.
- Breakdowns can occur.
- Are the answers worth anything?
- right and left eigenvectors
- residuals
- condition numbers for eigenvalues
- Don't skip these tests.

## **Example**

$$\bullet \ \lambda^2 Mv + \lambda Gv + Kv = 0$$

$$H = \begin{bmatrix} I & 0 \\ -\frac{1}{2}G & I \end{bmatrix} \begin{bmatrix} 0 & M^{-1} \\ -K & 0 \end{bmatrix} \begin{bmatrix} I & 0 \\ -\frac{1}{2}G & I \end{bmatrix}$$

$$H^{-1} = \begin{bmatrix} I & 0 \\ \frac{1}{2}G & I \end{bmatrix} \begin{bmatrix} 0 & (-K)^{-1} \\ M & 0 \end{bmatrix} \begin{bmatrix} I & 0 \\ \frac{1}{2}G & I \end{bmatrix}$$

#### Compare various approaches:

- Hamiltonian(1)  $H^{-1}$
- Hamiltonian(3)  $H^{-1}(H-\tau I)^{-1}(H+\tau I)^{-1}$
- symplectic  $(H \tau I)^{-1}(H + \tau I)$
- unstructured  $(H \tau I)^{-1}$ + ordinary Lanczos with implicit restarts

Get 6 smallest eigenvalues in right half-plane.

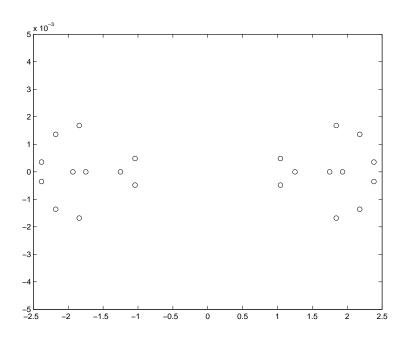
Tolerance = 
$$10^{-8}$$

Take 20 steps and restart with 10.

# No-Clue Case $(\tau = 0)$

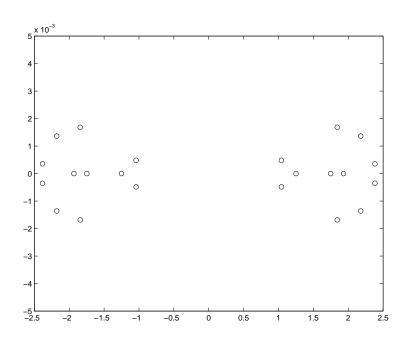
Method	Solves	Eigvals	Max.
		Found	Resid.
Hamiltonian(1)	78	9	$2\times10^{-10}$
Unstructured	158	7 + 7	$5 \times 10^{-7}$

Unstructured code must find everything twice.



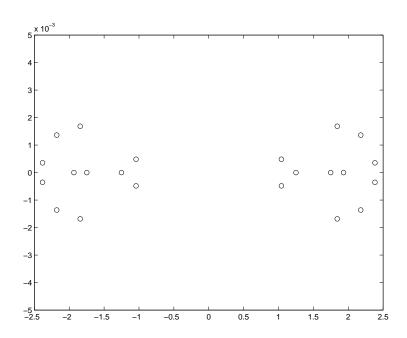
# Conservative Shift ( $\tau = 0.5$ )

Method	Solves	Eigvals	Max.
		Found	Resid.
Hamiltonian(1)	78	9	$2\times10^{-10}$
Unstructured	138	7 + 2	$3 \times 10^{-5}$
Hamiltonian(3)	174	11	$3 \times 10^{-13}$
Symplectic	156	11	$2 \times 10^{-8}$



# Aggressive Shift ( $\tau = 1.5$ )

Method	Solves	Eigvals	Max.
		Found	Resid.
Hamiltonian(1)	78	9	$2 \times 10^{-10}$
Unstructured	96	9	$1 \times 10^{-7}$
Hamiltonian(3)	120	9	$2 \times 10^{-12}$
Symplectic	156	11	$2 \times 10^{-11}$



#### The Last Slide

- We have developed structure-preserving implicitly-restarted Lanczos methods for Hamiltonian and symplectic eigenvalue problems.
- The structure-preserving methods are more accurate than a comparable non-structured method.
- By exploiting structure we can solve our problems more economically.