# An Iterative Method for Contour Based Nonlinear Eigensolvers

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## Beyn's Method

Use Keldysh theorem to probe Jordan decomposition for spectral information, giving a linearization of  $T(\lambda)$ .

$$A_k = \frac{1}{2\pi i} \int_{\Gamma} z^k T(z)^{-1} X \, dz = V \Lambda^k W^H X \tag{1}$$

Taking the SVD  $A_0=V_0\Sigma_0W_0^H$  we can derive the following (computable) similarity.

$$\Lambda \sim V_0^H A_1 W_0 \Sigma_0^{-1} \tag{2}$$

This gives a standard problem  $V_0^H A_1 W_0 \Sigma_0^{-1} Y = Y \Lambda$ , taking  $X = V_0 Y$  recovers eigenvectors.

#### **NLFEAST**

Applying a Residual Inverse Iteration with contour points as fixed shifts gives a Newton-type iteration.

$$Q_0 = \frac{1}{2\pi i} \int_{\Gamma} \left( X - T(z)^{-1} T(X, \Lambda) \right) (zI - \Lambda)^{-1} dz \tag{3}$$

Each iteration solve the projected problem.

$$Q_0^H T(\lambda) Q_0 y = 0 \tag{4}$$

Recover eigenvectors by taking  $X = Q_0Y$ .

#### **Problems**

- ► How to share contour nodes (and thus linear system solves) when using NLFEAST with Beyn?
- How can Beyn's method be iteratively refined? Doing so would address drawbacks of using many quadrature points.

#### NLFEAST-Beyn Hybrid Algorithm

We can generalize the RII moment  $Q_0$  of NLFEAST to  $Q_k$ .

$$Q_k = \frac{1}{2\pi i} \int_{\Gamma} z^k \Big( X - T(z)^{-1} T(X, \Lambda) \Big) (zI - \Lambda)^{-1} dz \qquad (5)$$

Then apply the linearization of Beyn's method to these moments.

## NLFEAST-Beyn Hybrid Algorithm

$$\begin{split} Q_0 &= \sum_{j=1}^N \omega_j T(z_j)^{-1} X \\ Q_1 &= \sum_{j=1}^N \omega_j z_j T(z_j)^{-1} X \\ \text{Compute the QR Decomposition } qr \leftarrow Q_0 \\ B &= q^H Q_1 r^{-1} \\ \text{Solve } BY &= Y \Lambda \\ X \leftarrow qY \\ \text{while not converged do} \\ Q_0 \leftarrow \sum_{j=1}^N \omega_j [X - T(z_j)^{-1} T(X, \Lambda)] (z_j I - \Lambda)^{-1} \\ Q_1 \leftarrow \sum_{j=1}^N \omega_j z_j [X - T(z_j)^{-1} T(X, \Lambda)] (z_j I - \Lambda)^{-1} \\ \text{Compute the QR Decomposition } qr \leftarrow Q_0 \\ B \leftarrow q^H Q_1 r^{-1} \\ \text{Solve } BY &= Y \Lambda \\ X \leftarrow qY \\ \text{end while} \\ \text{return } X, \Lambda \end{split}$$

#### NLFEAST-Beyn Hybrid Algorithm

- ► From one perspective, this can be viewed as NLFEAST using the linearization (from Keldysh) of Beyn's method directly.
- ► From the other, it can be viewed as Beyn's method using the RII (from Neumaier) approach of NLFEAST.
- Can be reduced to standard FEAST for linear problems.

#### **Higher Moments**

Necessary to use higher moments for eigenvector defects or many eigenvalues in a contour.

General way of considering most higher moment algorithms by considering "left probing matrix"  $\widehat{X} \in \mathbb{C}^{n \times \ell}$  in addition to "right probing matrix"  $X \in \mathbb{C}^{n \times m}$  and defining

$$\widehat{A}_k = \widehat{X}^H A_k = \frac{1}{2\pi i} \int_{\Gamma} z^k \widehat{X}^H T(z)^{-1} X \, dz. \tag{6}$$

## Higher Moment Matrix

Choosing  $K \in \mathbb{N}$  as the number of computed moments, form the  $K\ell \times Km$  block Hankel matrices

$$H_0 = \begin{bmatrix} \widehat{A}_0 & \cdots & \widehat{A}_{K-1} \\ \vdots & & \vdots \\ \widehat{A}_{K-1} & \cdots & \widehat{A}_{2K-2} \end{bmatrix}, H_1 = \begin{bmatrix} \widehat{A}_1 & \cdots & \widehat{A}_K \\ \vdots & & \vdots \\ \widehat{A}_K & \cdots & \widehat{A}_{2K-1} \end{bmatrix}. \quad (7)$$

From the Keldysh theorem we have  $\widehat{A}_k = \widehat{X} V \Lambda^k W^H X$  , letting

$$V_{[K]} = \begin{bmatrix} \widehat{X}V\\ \vdots\\ \widehat{X}V\Lambda^{K-1} \end{bmatrix}, \quad W_{[K]}^H = \begin{bmatrix} W^HX, \dots, \Lambda^{K-1}W^HX \end{bmatrix} \quad (8)$$

we have, similarly to before with  $A_0$  and  $A_1$ , that

$$H_0 = V_{[K]} W_{[K]}^H, \quad H_1 = V_{[K]} \Lambda W_{[K]}^H.$$
 (9)

#### Higher Moment Methods

Using the same similarity as Beyn's method, taking the SVD  $H_0=V_0\Sigma_0W_0^H$ , we can diagonalize  $V_0^HH_1W_0\Sigma_0^{-1}$  to find  $\Lambda.$  Recovering the eigenvectors depends on the form of  $\widehat{X}$ .

- ▶ Taking  $\widehat{X} = I \in \mathbb{C}^{n \times n}$  gives Beyn's method.
- ▶ Taking  $\widehat{X} = X$  gives the SS-Hankel method. Here  $H_0, H_1$  are square and another approach is need to recover eigenvectors.

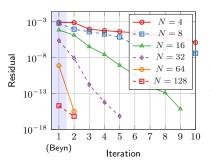
For  $\widehat{X}=I$  (thus  $\widehat{A}_k=A_k$ ) we have applied the RII method. This requires deflating the subspace after every iteration.

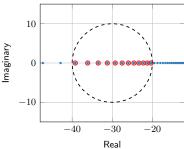
#### Problems with Higher Moments

- ► Eigenvectors (potentially) only recoverable in special cases, limiting iteration to Beyn and SS type methods.
- SS-Hankel approach has benefits, but not yet explored.
- Deflation after every iteration limits number of eigenvalues. Unclear how RII can be modified to reuse all spectral information after iteration.
- No way to determine when there are deficient eigenvectors without computing many higher moments.

## **Numerical Experiments**

#### Hadeler Problem





#### **Numerical Experiments**

#### **Butterfly Problem**

