

Solving Large Sparse Linear and Quadratic Generalized Eigenvalue Problems*

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We study the methods for solving the following large order eigenvalue problems occurring in the analysis of structural vibration^[3,4,12]:

$$(K - \lambda M)x = 0, \quad (1)$$

$$(M\lambda^2 - C\lambda - K)x = 0 \quad (2)$$

and

$$(M\lambda^2 + \tilde{C}\lambda + K)x = 0, \quad (3)$$

where M and C are both symmetric matrices, while \tilde{C} is skew symmetric. Moreover, M is positive definite, and the matrix K in (2) and (3) is also assumed to be symmetric positive definite.

I The eigenvalue problem for normal matrices in generalized inner product
Let B be an $n \times n$ Hermitian positive definite matrix. Then

$$\langle x, y \rangle \equiv (x, By) \equiv y^H Bx \quad (4)$$

is called B -inner product. We can define B -norm, B -normal matrix, B -Hermitian matrix, B -skew Hermitian matrix and B -unitary matrix as usual.

Theorem 1 $n \times n$ matrix G is B -normal if and only if

$$B^{-1}G^H B G = G B^{-1} G^H B. \quad (5)$$

While the fact that G is B -Hermitian, B -skew Hermitian or B -unitary is characterized by $G^H B = B G$, $G^H B = -B G$ or $G^H B = B G^{-1}$ respectively. If $n \times m$ matrix F consists of m B -orthonormal vectors as its columns, then the project matrix of G determined by F is $F^H B G F$. If G is B -normal, then it has a full B -orthonormal system of eigenvectors. If the B -unitary matrix with these eigenvectors as its columns is denoted by Q , and the diagonal matrix consisting of the corresponding eigenvalue is denoted by Λ , then

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$$Q^H B G Q = A, \quad Q^H G^H B Q = \bar{A}. \quad (6)$$

Poof Suppose G corresponds to an operator and the matrix corresponding to the conjugate operator in the B -inner product is G^* , then from

$$\langle Gx, y \rangle_B = \langle x, G^*y \rangle_B,$$

we have

$$(Gx, By) = (x, BG^*y),$$

that is

$$G^* = B^{-1}G^H B. \quad (7)$$

From this we can easily arrive at all the conclusions of the theorem. Q. E. D.

Corollary If G is B -normal, then G^*G and G have a common full B -orthonormal system of eigenvectors.

Theorem 2 Suppose X is the $n \times p$ matrix whose columns are composed of p vectors from a B -orthonormal basis of the invariant subspace for the B -normal matrix G . Then the B -orthogonal project matrix $X^H B G X$ of G determined by X is normal.

Proof Let the columns of the $n \times (n-p)$ matrix Y be the basis of the B -orthogonal complement to the space spanned by the columns of X . We have

$$Y^H B X = 0, \quad X^H B Y = 0, \\ \begin{bmatrix} X^H \\ Y^H \end{bmatrix} B \begin{bmatrix} X \\ Y \end{bmatrix} = I \quad (8)$$

and

$$\begin{bmatrix} X^H \\ Y^H \end{bmatrix} B G \begin{bmatrix} X \\ Y \end{bmatrix} = \begin{bmatrix} X^H B G X & \\ & Y^H B G Y \end{bmatrix}. \quad (9)$$

Let $\begin{bmatrix} X \\ Y \end{bmatrix} = B^{-1/2} \begin{bmatrix} \tilde{X} \\ \tilde{Y} \end{bmatrix}$, then from (8) we have

$$\begin{bmatrix} \tilde{X}^H \\ \tilde{Y}^H \end{bmatrix} \begin{bmatrix} \tilde{X} \\ \tilde{Y} \end{bmatrix} = I = \begin{bmatrix} \tilde{X} \\ \tilde{Y} \end{bmatrix} \begin{bmatrix} \tilde{X}^H \\ \tilde{Y}^H \end{bmatrix}, \quad (10)$$

from (9) it follows that

$$R \equiv \begin{bmatrix} \tilde{X}^H \\ \tilde{Y}^H \end{bmatrix} B^{1/2} G B^{-1/2} \begin{bmatrix} \tilde{X} \\ \tilde{Y} \end{bmatrix} = \begin{bmatrix} \tilde{X}^H B G \tilde{X} & \\ & \tilde{Y}^H B G \tilde{Y} \end{bmatrix}. \quad (11)$$

But from (10) and (5) we get

$$R^H R = \begin{bmatrix} \tilde{X}^H \\ \tilde{Y}^H \end{bmatrix} B^{-1/2} G^H B G B^{-1/2} \begin{bmatrix} \tilde{X} \\ \tilde{Y} \end{bmatrix} = \begin{bmatrix} \tilde{X}^H \\ \tilde{Y}^H \end{bmatrix} B^{1/2} G B^{-1} G^H B^{1/2} \begin{bmatrix} \tilde{X} \\ \tilde{Y} \end{bmatrix} = R R^H.$$

By (11) we also have

$$(X^H B G X)^H (X^H B G X) = (X^H B G X) (X^H B G X)^H. \quad \text{Q. E. D.}$$

From theorem 1 and its corollary and theorem 2 we can derive the following
Algorithm I (Subspace Iteration Method for B-normal Matrices)

(1) Take p random initial vectors ($q \leq p < n$), B-orthonormalize them, and denote the resulting $n \times p$ matrix by $X^{(0)}$, that is, $X^{(0)H}BX^{(0)} = I_p$.

(2) If the $(\nu-1)$ -th matrix $X^{(\nu-1)}$ has been obtained, then the iterative procedure for finding $X^{(\nu)}$ is as follows

- (i) Compute $Z^{(\nu)} = GX^{(\nu-1)}$,
- (ii) Compute $p \times p$ Hermitian positive definite matrix $S^{(\nu)} = Z^{(\nu)H}BZ^{(\nu)}$,
- (iii) Find all the eigenvalues and eigenvectors of $S^{(\nu)}$.

$$Q^{(\nu)H}S^{(\nu)}Q^{(\nu)} = (D^{(\nu)})^2,$$

where $Q^{(\nu)}$ is a $p \times p$ unitary matrix, $D^{(\nu)}$ is a diagonal matrix with positive diagonal elements which are ordered decreasingly.

(iv) Compute $X^{(\nu+1)} = Z^{(\nu)}Q^{(\nu)}(D^{(\nu)})^{-1}$,

(v) Test the convergence.

(3) Denote $X^{(\nu)}$ which has converged by X . Partition X as $X = [X_1, \dots, X_m]$, where each X_i corresponds to the eigenvalues which have an equal modulus. Compute the B-project matrix $X_i^H B G X_i$ of G determined by X_i , and solve the eigenvalue problem of the lower order normal matrix:

$$P_i^H (X_i^H B G X_i) P_i = \Lambda_i.$$

At the end of this step we obtain eigenvector matrix $X_i P_i$ and eigenvalue diagonal matrix Λ_i .

Remark The analysis of the convergence in [8, 11] may be adopted to the present algorithm, provided that the usual norm is replaced by B-norm. It is the generalization of that in [8]. McCormick and Noe have made an analogous generalization [6]. Obviously, our way of generalization is more straightforward.

For some special B-normal matrix G we can derive the following algorithm (provided that they satisfy the condition: for any matrix Q with B-orthonormal columns $Q^H B G Q$ is normal. For example, if G is B-Hermitian or B-skew Hermitian, then the condition is satisfied.)

Algorithm II (Subspace Iteration Method for B-normal Matrix)

(1) Take p random initial vectors ($q \leq p < n$), B-orthonormalize them, and denote the resulting $n \times p$ matrix by $X^{(0)}$, that is, $X^{(0)H}BX^{(0)} = I_p$.

(2) If the $(\nu-1)$ -th matrix $X^{(\nu-1)}$ has been obtained, then the iterative procedure for finding $X^{(\nu)}$ is as follows

- (i) Compute $Z^{(\nu)} = GX^{(\nu-1)}$,
- (ii) B-orthonormalize the columns of $Z^{(\nu)}$ and get $Q^{(\nu)}$.

$$Z^{(r)} = Q^{(r)} R^{(r)},$$

where the columns of $Q^{(r)}$ are B-orthonormal, and $R^{(r)}$ is a $p \times p$ upper triangular matrix.

(iii) Compute B-orthogonal project matrix $S^{(r)}$ of G determined by $Q^{(r)}$

$$S^{(r)} = Q^{(r)H} B G Q^{(r)}.$$

(iv) Solve the eigenvalue problem for the lower order normal matrix $S^{(r)}$:

$$P^{(r)H} S^{(r)} P^{(r)} = \Lambda^{(r)}.$$

(v) Compute $X^{(r)} = Q^{(r)} P^{(r)}$.

(iv) Test the convergence.

Remarks 1. When B is real and G is B-symmetric (or B-skew symmetric), then

$$S^{(r)} = Q^{(r)T} B G Q^{(r)}$$

is real symmetric (or skew symmetric). We can use the Jacobi-like algorithm in [10] to perform step (2) (iv). The whole procedure of computation can be performed with real arithmetic.

2. By an argument analogous to that used in [10] we can prove the convergence of algorithm II. When G is B-normal, the convergence rate is the same as when G is symmetric.

For general B-normal matrix G , the Lanczos algorithm follows the same procedure as that of algorithm I: First, by applying Lanczos algorithm to G^*G we obtain some extreme eigenvalues and their corresponding eigenvectors. Then, by using the B-orthogonal project metrics determined by the invariant subspaces spanned by the eigenvectors corresponding to the eigenvalues with equal modulus, we can obtain the eigenvalues and the eigenvectors of G .

The recurrence relation of Lanczos algorithm for G^*G is

$$\beta_{j+1} B v_{j+1} = G^H B G v_j - \alpha_j B v_j - \beta_j B v_{j-1},$$

and the corresponding matrix form is

$$G^H B G V_j = B V_j T_j + \beta_{j+1} B v_{j+1} e_j,$$

where $V_j = [v_1, \dots, v_j]$ and T_j is a symmetric three diagonal matrix

$$T_j = V_j^H G^H B G V_j = \begin{pmatrix} \alpha_1 & \beta_2 & & \\ \beta_2 & \alpha_2 & \beta_3 & \\ & \ddots & \ddots & \ddots \\ & & \beta_j & \alpha_j \end{pmatrix}$$

For B-Hermitian G we can implement Lanczos algorithm directly to G , the recurrence relation is

$$\beta_{j+1}v_{j+1} = Gv_j - \alpha_jv_j - \beta_jv_{j-1}.$$

The corresponding matrix form is

$$GV_j = V_jT_j + \beta_{j+1}v_{j+1}e_j,$$

and the three diagonal matrix T_j is

$$T_j = V_j^H BGV_j.$$

For B-skew Hermitian G , owing to the fact that iG is B-Hermitian, we can implement the Lanczos algorithm to iG .

II Generalized eigenvalue problem

By taking M as the matrix B in the previous section we can transform the linear generalized eigenvalue problem (1) into a standard eigenvalue problem in M -inner product:

$$G_1X \equiv M^{-1}(K - \sigma M)x = \lambda x \quad (12)$$

or

$$G_2X \equiv (K - \sigma M)^{-1}Mx = \lambda x. \quad (13)$$

If K is such that G_1 or G_2 is M -normal, then we can apply the algorithm in the previous section in solving problems (12) and (13). Particularly, when K is Hermitian, and σ is a real scalar, G_1 and G_2 are M -Hermitian. When K is skew Hermitian and σ is a pure imaginary scalar, G_1 and G_2 are M -skew Hermitian.

For quadratic generalized eigenvalue problem (2) and (3), we can respectively transform them into the following linear generalized eigenvalue problems^[3, 4, 12]

$$\begin{bmatrix} O & K \\ K & C \end{bmatrix} \begin{bmatrix} x \\ \lambda x \end{bmatrix} = \lambda \begin{bmatrix} K \\ M \end{bmatrix} \begin{bmatrix} x \\ \lambda x \end{bmatrix} \quad (14)$$

and

$$\begin{bmatrix} O & K \\ -K & -\tilde{C} \end{bmatrix} \begin{bmatrix} x \\ \lambda x \end{bmatrix} = \lambda \begin{bmatrix} K \\ M \end{bmatrix} \begin{bmatrix} x \\ \lambda x \end{bmatrix}. \quad (15)$$

The problem (14) in which $\begin{bmatrix} O & K \\ K & C \end{bmatrix}$ is symmetric has been studied in [9]. We now study the method for solving problem (3) i. e. problem (14), (15) may be abbreviated to

$$Ay = \lambda By, \quad (16)$$

where B is symmetric positive definite, A is skew symmetric and A and B are of the forms presented by (15).

Theorem 3 The eigenvalues of the quadratic problem (3) are all nonzero

pure imaginary scalars with a half of them on the positive imaginary semi-axis and the other half on the negative imaginary semi-axis.

Proof Make Cholesky decomposition $B = LL^T$, where L is nonsingular lower triangular. (16) is equivalent to

$$(L^{-1}AL^{-T})\tilde{y} = \lambda\tilde{y}. \quad (17)$$

It is easy to show that A is nonsingular. Also,

$$iA = \begin{bmatrix} O & iK \\ -iK & -i\tilde{C} \end{bmatrix}$$

is Hermitian. By applying Poincaré separation theorem^[1,5] and considering the fact that iA is nonsingular we can see that iA has n positive eigenvalues and n negative eigenvalues. From (17), we may apply the inertia theorem and the conclusion of the theorem follows. Q. E. D.

It is most advantageous to take B-skew Hermitian matrix

$$(A - i\sigma B)^{-1}B, \quad (18)$$

where σ is a real scalar, in finding some of the eigenvalues which are near $i\sigma$ by the subspace algorithm or Lanczos algorithm discussed in the previous section. We shall show that it is not necessary to invert or to factorize a $2n \times 2n$ matrix (c.f. (18)).

Let

$$W(\sigma) = K + i\sigma\tilde{C} - \sigma^2 M. \quad (19)$$

Clearly, $W(\sigma)$ is an $n \times n$ Hermitian matrix. Then we may make the symmetric decomposition

$$W(\sigma) = LDL^H, \quad (20)$$

where D is a real diagonal matrix.

Theorem 4 Let σ be a real scalar such that the decomposition (20) is possible, then, (i) The number of the negative diagonal elements of D is equal to the number of the eigenvalues of problem (3) between 0 and $i\sigma$ on the imaginary axis.

$$(ii) \quad (A - i\sigma B)^{-1}B \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = i \begin{bmatrix} W^{-1}(\sigma) (i\tilde{C}x_1 - \sigma Mx_1 + iMx_2) \\ -W^{-1}(\sigma) (iKx_1 + \sigma Mx_2) \end{bmatrix}. \quad (21)$$

Proof When $\sigma \neq 0$, we have

$$iA + \sigma B = \begin{bmatrix} I & \\ & -iI/\sigma \end{bmatrix} \begin{bmatrix} \sigma K & \\ & -W(\sigma)/\sigma \end{bmatrix} \begin{bmatrix} I & iI/\sigma \\ & I \end{bmatrix}. \quad (22)$$

By applying the inertia theorem and theorem 3 the first assertion follows.

By (22) it is easy to get

$$\begin{aligned}
 (A - i\sigma B)^{-1}B \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} &= i \begin{bmatrix} I & -iI/\sigma \\ & I \end{bmatrix} \begin{bmatrix} K^{-1}/\sigma \\ -\sigma W^{-1}(\sigma) \end{bmatrix} \begin{bmatrix} I & \\ iI/\sigma & I \end{bmatrix} \begin{bmatrix} Kx_1 \\ Mx_2 \end{bmatrix} \\
 &= i \begin{bmatrix} x_1/\sigma + W^{-1}(\sigma)(-Kx_1/\sigma + iMx_2) \\ W^{-1}(\sigma)(-iKx_1 - \sigma Mx_2) \end{bmatrix} = i \begin{bmatrix} W^{-1}(\sigma)(i\tilde{C}x_1 - \sigma Mx_1 + iMx_2) \\ -W^{-1}(\sigma)(iKx_1 + \sigma Mx_2) \end{bmatrix}.
 \end{aligned}$$

When $\sigma = 0$, it is easy to check that (21) holds. Q. E. D.

From Theorem 4 it follows that for solving problem (3), if we take B-skew Hermitian $(A - i\sigma B)^{-1}B$ as the matrix G and apply subspace iteration algorithm I or II, or if we take B-Hermitian $(iA + \sigma B)^{-1}B$ as the matrix G and apply subspace iteration algorithm II or Lanczos algorithm, then it is only necessary to compute the triangular decomposition of the $n \times n$ Hermitian matrix $W(\sigma)$. Hence the presented algorithms for solving quadratic eigenvalue problem are quite efficient.

Particularly, if we want to find some eigenvalues with minimal moduli, then we may take $\sigma = 0$, and then $A^{-1}B$ is B-skew symmetric and $W(0) = K$. Thus we can use subspace iteration algorithm II and perform the whole procedure with real arithmetic.

Obviously, the algorithms for B-normal matrix presented in this paper can be used efficiently to solve the quadratic eigenvalue problems of a wide variety.

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