

# On the Eigenvalues Distribution of Preconditioned Block Two-by-two Matrix

Mu-Zheng Zhu<sup>†</sup> and Ya-E Qi<sup>‡</sup>

**Abstract**—The spectral properties of a class of block  $2 \times 2$  matrix are studied, which arise in the numerical solutions of PDE-constrained optimization problems. Based on the Schur complement approximate approach and inexact Uzawa preconditioner, the eigenvalues distribution of preconditioned matrix is discussed by the similarity transformation. Moreover, The numerical experiments originated in PDE-constrained optimization problem are presented to show that the theoretical bound of the eigenvalues is in good agreement with its practical bound.

**Index Terms**—block two-by-two linear systems, schur complement approach, inexact Uzawa preconditioner, eigenvalues distribution, PDE-constrained optimization problems.

## I. INTRODUCTION

**I**N this paper, we investigate spectral properties of block  $2 \times 2$  matrix in following linear systems:

$$\mathcal{A}x \equiv \begin{pmatrix} W & T \\ T & -W \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} f \\ g \end{pmatrix} \equiv b, \quad (1)$$

where  $W, T \in \mathbb{R}^{n \times n}$  are symmetric positive semi-definite (SPSD) and one of them is symmetric positive definite (SPD). Without loss of generality, we assume  $W$  is SPD. The matrix  $\mathcal{A}$  is nonsingular if and only if  $\text{null}(W) \cap \text{null}(T) = \{0\}$  [10]. Thus, the linear system (1) has a unique solution when the (1, 1)-block in matrix  $\mathcal{A}$  is nonsingular.

The linear system (1) can be formally regard as a special case of the saddle point problems [5]–[7]. They frequently arise from finite element discretizations of PDE-constrained optimization problems [7], [10], [23], [31], complex symmetric linear systems [2], [8], [9], [11], finite element discretizations of first-order linearization of the two-phase flow problems based on Cahn-Hilliard equation [4], [16], matrix completions problems [18], and so on [6], [12], [24], [26]. A large variety of applications and numerical solution methods of linear system (1) have been comprehensively reviewed by Benzi, Golub, and Liesen [12].

In recent years, the eigenvalue distribution of block  $2 \times 2$  linear systems has been deeply studied [1], [13], [14], [22], [29]. On the one hand, the bounds for eigenvalues of  $\mathcal{A}$  in (1) can be used to analyze the spectral properties

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of preconditioners such as symmetric indefinite preconditioners, inexact constraint preconditioners and primal-based penalty preconditioners for linear systems (1); see [13]–[15], [21], [28]. On the other hand, the estimates for eigenvalues of  $\mathcal{A}$  in (1) can give theoretical basis for the CG method solving linear system (1) in a nonstandard inner product; see [20], [27], [28].

Our focus is on an important block lower triangular preconditioner, called inexact Uzawa preconditioner, which exploit the knowledge of a good approximation for the (negative) Schur complement. The aim of this paper is to investigate the spectral properties and provide the eigenvalues distribution of preconditioned matrix.

The remainder of this paper is organized as follows. In Section II, an new Schur approximation with parameter is presented and the approximate degree is studied. In Section III, an inexact Uzawa preconditioner is introduced and the eigenvalues distribution of preconditioned matrix are analyzed by the use of a similarity transformation. In Section IV, the numerical experiments are given to show that the theoretical bound of eigenvalues distribution is in good agreement with the practical bound though PDE-constrained optimization problems. Finally, in Section V we end this paper with some conclusions.

## II. SCHUR COMPLEMENT APPROXIMATE

**I**N this section, we consider the approximate degree between the Schur complement  $S := W + TW^{-1}T$  of the matrix  $\mathcal{A}$  and its approximate

$$S(\alpha) = (W + \alpha T)W^{-1}(W + \alpha^* T),$$

where  $\text{Re}(\alpha) > 0$  and  $\alpha\alpha^* = 1$ .

As  $W^{-\frac{1}{2}}TW^{-\frac{1}{2}}$  is symmetric positive semi-definite, then an orthogonal matrix  $Q \in \mathbb{R}^{n \times n}$  and a diagonal matrix  $\Sigma = (\sigma_{ii})_{n \times n}$ ,  $\sigma_{ii} \geq 0$  are exist to such that

$$W^{-\frac{1}{2}}TW^{-\frac{1}{2}} = Q^T \Sigma Q,$$

so the following expression is true:

$$\begin{aligned} S(\alpha)^{-1} &= (W + \alpha^* T)^{-1} W (W + \alpha T)^{-1} \\ &= W^{-\frac{1}{2}} (I + 2\text{Re}(\alpha) Q^T \Sigma Q + Q^T \Sigma^2 Q)^{-1} W^{-\frac{1}{2}} \\ &= (QW^{-\frac{1}{2}})^{-1} (I + 2\text{Re}(\alpha) \Sigma + \Sigma^2)^{-1} (QW^{-\frac{1}{2}}). \end{aligned}$$

It is obvious that  $S = S(\mathbf{i})$ , where  $\mathbf{i} = \sqrt{-1}$  is the imaginary unit. Thus,

$$S = W^{\frac{1}{2}} Q^T (I + \Sigma^2) Q W^{-\frac{1}{2}}.$$

Then

$$S(\alpha)^{-1} S = (QW^{-\frac{1}{2}})^{-1} H (QW^{-\frac{1}{2}}), \quad (2)$$

where  $H = (1 + \text{Re}(\alpha)\Sigma + \Sigma^2)^{-1}(I + \Sigma^2)$  is a diagonal matrix and its diagonal elements

$$h_{ii} = \frac{1 + \sigma_{ii}^2}{1 + 2\text{Re}(\alpha)\sigma_{ii} + \sigma_{ii}^2} \leq 1,$$

and the equality hold up if and only if  $\text{Re}(\alpha) = 0$ .

It can be found from (2) that  $S(\alpha)^{-1}S$  and  $H$  have the same eigenvalues. According

$$\begin{aligned} h_{ii} &= \frac{1 + \sigma_{ii}^2}{1 + 2\text{Re}(\alpha)\sigma_{ii} + \sigma_{ii}^2} \geq \frac{1}{1 + \frac{2\text{Re}(\alpha)\sigma_{ii}}{1 + \sigma_{ii}^2}} \\ &\geq \frac{1}{1 + \text{Re}(\alpha)} \quad (1 \leq i \leq n), \end{aligned}$$

we easily have

$$\lambda(S(\alpha)^{-1}S) \in \left[ \frac{1}{1 + \text{Re}(\alpha)}, 1 \right]. \quad (3)$$

Similarly, an approximation  $\widehat{W}$  can be found for  $W$ , and  $\lambda(\widehat{W}^{-1}W) \in [\underline{\mu}, \bar{\mu}]$ , where  $\underline{\mu} > 0, \bar{\mu} < 1$ .

### III. PRECONDITIONER AND EIGENVALUES DISTRIBUTION

**T**HERE are many "indefinite" preconditioner with block  $2 \times 2$  form are presented, whose indefiniteness is tailored to compensate for the indefiniteness of systems matrix, and in this sense that the preconditioned matrix has only eigenvalues with positive real part. The eigenvalue distribution for this type preconditioners with Schur complement are also widely discussed. These include indefinite block diagonal preconditioners [13], [19], block triangular preconditioners [30], for inexact Uzawa preconditioners [17], and block approximate factorization preconditioners [3].

Our focus is on the inexact Uzawa preconditioner

$$\widehat{M} = \begin{pmatrix} \widehat{W} & 0 \\ T & -S(\alpha) \end{pmatrix} = \begin{pmatrix} I_n & 0 \\ T\widehat{W}^{-1} & I_n \end{pmatrix} \begin{pmatrix} \widehat{W} & \\ & -S(\alpha) \end{pmatrix}, \quad (4)$$

which is considered in [24]. The eigenvalues distribution of the preconditioned matrix  $\widehat{M}^{-1}\mathcal{A}$  are discussed in this section.

When  $\widehat{W} = W$  and  $S(\alpha) = S$ , it is well known that the preconditioner (4) is such that the preconditioned matrix has all eigenvalues equal to 1 and minimal polynomial of degree at most 2 [12].

However, using these "ideal" preconditioners requires exact solves with  $W$  and  $S$ , which is often impractical, just the computation of  $S$  can be prohibitive [24]. Here we investigate the effect of using approximations  $S(\alpha)$  instead Schur complement  $S$ . We analyze how the eigenvalue distributions are affected by providing bounds, where "bounds" for non-real eigenvalues, have to be understood as combinations of inequalities proving their clustering in a confined region of the complex plane.

Assume  $Y \in \mathbb{R}^{n \times n}$  is an orthogonal matrix,  $V < I$  ( $V = \text{diag}(v_1, v_2, \dots, v_n)$ ,  $v_1 \leq v_2 \leq \dots \leq v_n < 1$ ) is a diagonal matrix such that  $Y^T W^{\frac{1}{2}} \widehat{W}^{-1} W^{\frac{1}{2}} Y = V$ . Then

$$\begin{aligned} \widehat{M}^{-1}\mathcal{A} &= \begin{pmatrix} \widehat{W} & \\ & -S(\alpha) \end{pmatrix}^{-1} \begin{pmatrix} I_n & 0 \\ -T\widehat{W}^{-1} & I_n \end{pmatrix} \begin{pmatrix} W & T \\ T & -W \end{pmatrix} \\ &= \begin{pmatrix} \widehat{W}^{-1} & \\ & S(\alpha)^{-1} \end{pmatrix} \begin{pmatrix} W & T \\ -T(I - \widehat{W}^{-1}W) & (W + T\widehat{W}^{-1}T) \end{pmatrix}. \end{aligned}$$

As  $Y^T W^{\frac{1}{2}} \widehat{W}^{-1} W^{\frac{1}{2}} Y = V$ , we have

$$\begin{aligned} &\begin{pmatrix} Y^T W^{\frac{1}{2}} & \\ & S(\alpha)^{\frac{1}{2}} \end{pmatrix} \begin{pmatrix} \widehat{W}^{-1} & \\ & S(\alpha)^{-1} \end{pmatrix} \begin{pmatrix} W^{-\frac{1}{2}} Y & \\ & S(\alpha)^{\frac{1}{2}} \end{pmatrix} \\ &\cdot \begin{pmatrix} Y^T W^{-\frac{1}{2}} & \\ & S(\alpha)^{-\frac{1}{2}} \end{pmatrix} \begin{pmatrix} W & T \\ -T(I - \widehat{W}^{-1}W) & (W + T\widehat{W}^{-1}T) \end{pmatrix} \\ &\cdot \begin{pmatrix} W^{-\frac{1}{2}} Y & \\ & S(\alpha)^{-\frac{1}{2}} \end{pmatrix} \\ &= \begin{pmatrix} V & \\ & I \end{pmatrix} \begin{pmatrix} Y^T W^{-\frac{1}{2}} & -Y^T W^{-\frac{1}{2}} T \\ -S(\alpha)^{-\frac{1}{2}} T(I - \widehat{W}^{-1}W) & S(\alpha)^{-\frac{1}{2}} (W + T\widehat{W}^{-1}T) \end{pmatrix} \\ &\cdot \begin{pmatrix} W^{-\frac{1}{2}} Y & \\ & S(\alpha)^{-\frac{1}{2}} \end{pmatrix} \\ &= \begin{pmatrix} V & \\ & I \end{pmatrix} \begin{pmatrix} I & G^T \\ -G(I - V) & (\widehat{C} + GVG^T) \end{pmatrix} =: J, \end{aligned}$$

where  $G = S(\alpha)^{-\frac{1}{2}} T W^{-\frac{1}{2}} Y$ ,  $\widehat{C} = S(\alpha)^{-\frac{1}{2}} W S(\alpha)^{-\frac{1}{2}}$ .

It is evident that  $\widehat{C} + GVG^T = S(\alpha)^{-\frac{1}{2}} S S(\alpha)^{-\frac{1}{2}}$ , i.e.,

$$\lambda(\widehat{C} + GVG^T) \in \left[ \frac{1}{1 + \text{Re}(\alpha)}, 1 \right].$$

According the assumption  $V < I$ ,  $V^{\frac{1}{2}}$  and  $(I - V)^{\frac{1}{2}}$  exist. Taking a similar transformation with respect to  $\text{blkdiag}((I - V)^{\frac{1}{2}} V^{-\frac{1}{2}}, I)$  on  $J$ , we have

$$\begin{aligned} &\begin{pmatrix} (I - V)^{\frac{1}{2}} V^{-\frac{1}{2}} & \\ & I \end{pmatrix} J \begin{pmatrix} V^{\frac{1}{2}} (I - V)^{-\frac{1}{2}} & \\ & I \end{pmatrix} \\ &= \begin{pmatrix} V & (V - V^2)^{\frac{1}{2}} G^T \\ -G(V - V^2)^{\frac{1}{2}} & (\widehat{C} + GVG^T) \end{pmatrix} \quad (5) \\ &\triangleq: \begin{pmatrix} A & B^T \\ -B & C \end{pmatrix} = K \end{aligned}$$

where  $A = V$  and  $C = \widehat{C} + GVG^T$  are all SPD,  $B = G(\Sigma - \Sigma^2)^{\frac{1}{2}}$ .

Such matrices are nonnegative definite in  $\mathbb{R}^n$ . Hence, their eigenvalues have positive real part [24]. Thus, if the preconditioned matrix is similar to a matrix of the above form (5), the indefiniteness of the original matrix (1) is lost. However, we must note that this is at the expense of the loss of the symmetry, meaning that a portion of the eigenvalues will be in general complex.

According the above discuss,  $\widehat{M}^{-1}\mathcal{A}$  is similar to the matrix of the form  $K$ , thus the eigenvalue analysis of the preconditioned matrix  $\widehat{M}^{-1}\mathcal{A}$  can be reduced to that of the matrix of the form  $K$ . Nextly the eigenvalues distribution of the preconditioned matrix is discussed and the main results is given.

**Lemma 1.** ([24]) Define

$$K = \begin{pmatrix} A & B^T \\ -B & C \end{pmatrix},$$

where  $A \in \mathbb{R}^{n \times n}$  is SPD,  $C \in \mathbb{R}^{m \times m}$  is positive semi-definite,  $m \leq n$ . Assume  $B$  has full rank or  $C$  is positive definite in null space of  $B^T$ . Let  $S_C = C + BA^{-1}B^T$ , and  $S_A = A + B^T C^{-1}B$  when  $C$  is positive definite, then the real eigenvalues  $\lambda$  of  $K$  satisfies the following condition:

$$\min(\lambda_{\min}(A), \lambda_{\min}(S_C)) \leq \lambda \leq \max(\lambda_{\max}(A), \lambda_{\max}(C)).$$

The non-real eigenvalues of  $K$  satisfies the following condition:

$$\frac{1}{2}(\lambda_{\min}(A) + \lambda_{\min}(C)) \leq \text{Re}(\lambda) \leq \frac{1}{2}(\lambda_{\max}(A) + \lambda_{\max}(C))$$

$$|\text{Im}(\lambda)| \leq (\lambda_{\max}(BB^T))^{\frac{1}{2}}, \quad \text{and} \quad |\lambda - \xi| \leq \xi,$$

where

$$\xi = \begin{cases} \frac{\lambda_{\max}(S_A) \lambda_{\max}(S_C)}{\lambda_{\max}(S_A) + \lambda_{\max}(S_C)}, & C \text{ is positive definite,} \\ \lambda_{\max}(S_C), & \text{otherwise.} \end{cases}$$

**Theorem 2.** The real eigenvalues  $\lambda$  of the inexact Uzawa preconditioned matrix  $\widehat{M}^{-1}\mathcal{A}$  satisfy

$$\min\left(v_1, \frac{1}{1 + \text{Re}(\alpha)}\right) \leq \lambda \leq 1.$$

The non-real eigenvalues  $\lambda$  of the inexact Uzawa preconditioned matrix  $\widehat{M}^{-1}\mathcal{A}$  satisfy

$$\frac{1}{2}\left(v_1 + \frac{1}{1 + \text{Re}(\alpha)}\right) \leq \text{Re}(\lambda) \leq \frac{1}{2}(v_n + 1),$$

$$|\text{Im}(\lambda)| \leq \frac{1}{2}\left(\frac{\sigma_n^2}{1 + 2\text{Re}(\alpha)\sigma_n + \sigma_n^2}\right)^{\frac{1}{2}},$$

and

$$\left|\lambda - \frac{1}{2}\right| \leq \frac{1}{2}.$$

Here,  $v_1, v_n$  is the minimum and maximum diagonal element of matrix  $V$  mentioned above respectively,  $\sigma_n$  is the maximum diagonal element of matrix  $\Sigma$  mentioned above.

**Proof.** As  $A$  and  $C$  are all positive definite matrices, the condition in Lemma 1 is satisfied. Now we consider

$$\sigma_{\max}(B) = \left(\lambda_{\max}(BB^T)\right)^{\frac{1}{2}}.$$

As  $B = G(V - V^2)^{\frac{1}{2}}$ , we have

$$\lambda_{\max}(BB^T) = \lambda_{\max}(G(V - V^2)G^T) \leq \frac{1}{4}\lambda_{\max}(GG^T)$$

$$\leq \frac{1}{4} \frac{\sigma_n^2}{1 + 2\text{Re}(\alpha)\sigma_n + \sigma_n^2}.$$

Then we have

$$|\text{Im}(\lambda)| \leq \frac{1}{2}\left(\frac{\sigma_n^2}{1 + \text{Re}(\alpha)\sigma_n + \sigma_n^2}\right)^{\frac{1}{2}}.$$

Because  $A = V < I$ ,  $W > \widehat{W}$ , i.e.,  $\widehat{W}^{-1} > W^{-1}$ . Thus the following expression is true:

$$C = S(\alpha)^{-\frac{1}{2}}(W + T\widehat{W}^{-1}T)S(\alpha)^{-\frac{1}{2}} \geq S(\alpha)^{-\frac{1}{2}}SS(\alpha)^{-\frac{1}{2}} \geq \frac{1}{1 + \text{Re}(\alpha)}I.$$

As  $C = \widehat{C} + GVG^T < \widehat{C} + GG^T < I$ , we have

$$\frac{1}{1 + \text{Re}(\alpha)} \leq \lambda < 1.$$

Next the eigenvalues distribution of  $S_C$ ,  $S_A$  is discussed. To analyze the Schur complement  $S_C$ , one firstly has to obtain it explicitly. One way is to consider the Schur complement,

$$S_C = C + BA^{-1}B^T = \widehat{C} + GVG^T + G(V - V^2)V^{-1}G^T = \widehat{C} + GG^T,$$

then  $\lambda(S_C) = \lambda(S(\alpha)^{-1}S)$  holds. As seen in formula (3), we have

$$\lambda(S_C) \in \left[\frac{1}{1 + \text{Re}(\alpha)}, 1\right].$$

Because

$$S_A = A + B^TC^{-1}B$$

$$= V^{\frac{1}{2}}(I + (I - V)^{\frac{1}{2}}G^T(\widehat{C} + GVG^T)^{-1}G(I - V)^{\frac{1}{2}})V^{\frac{1}{2}}$$

$$= V^{\frac{1}{2}}RV^{\frac{1}{2}},$$

we obtain the following result by using the Sherman-Morrison-Woodbury formula (SMW):

$$R^{-1} = I - (I - V)^{\frac{1}{2}}G^T \cdot [\widehat{C} + GVG^T + G(I - V)G^T]^{-1}G(I - V)^{\frac{1}{2}}$$

$$= I - (I - V)^{\frac{1}{2}}G^T(\widehat{C} + GG^T)^{-1}G(I - V)^{\frac{1}{2}}.$$

As  $G^T(\widehat{C} + GG^T)^{-1}G$  and  $GG^T(\widehat{C} + GG^T)^{-1}$  have the same set of nonzero eigenvalues and they are banded by

$$\max_x \frac{x^T GG^T x}{x^T(\widehat{C} + GG^T)x} \leq 1.$$

One then finds  $R^{-1} \geq I - (I - V)^{\frac{1}{2}}(I - V)^{\frac{1}{2}} = V$ , i.e.,  $H \leq V^{-1}$ . Further, we have  $\lambda(S_A) \leq 1$ .

Thus,

$$\xi = \frac{\lambda_{\max}(S_A)\lambda_{\max}(S_C)}{\lambda_{\max}(S_A) + \lambda_{\max}(S_C)} = \frac{1}{2}. \quad \square$$

Indeed, when  $W$  is trivial, more special conclusion can be reached.

**Corollary 3.** If  $\widehat{W} = W$  then  $V = I$ , the matrix

$$K = \begin{pmatrix} I & \\ & C + GG^T \end{pmatrix}$$

has only real eigenvalues, and the distribution of eigenvalues is

$$\lambda(K) \in \left[\frac{1}{1 + \text{Re}(\alpha)}, 1\right].$$

#### IV. NUMERICAL RESULTS

**I**N this section, it is illustrated by using numerical examples that the theoretical bound for eigenvalues of preconditioned matrix are agreement with its practical bound. All the tests are performed in MATLAB R2013a with machine precision  $10^{-16}$ .

we consider the distributed control problem which consists of a cost functional (6) to be minimized subject to a partial differential equation (PDE) problem posed on a domain  $\Omega \subset \mathbb{R}^2$  [25], [31]:

$$\min_{u, f} \frac{1}{2} \|u - u_*\|_2^2 + \beta \|f\|_2^2, \quad (6)$$

$$\text{subject to } -\nabla^2 u = f, \quad \text{in } \Omega = [0, 1]^2, \quad (7)$$

$$\text{with } u = u_*, \quad \text{on } \partial\Omega, \quad (8)$$

where the function

$$u_* = \begin{cases} (2x - 1)^2(2y - 1)^2, & (x, y) \in [0, \frac{1}{2}]^2, \\ 0, & \text{otherwise,} \end{cases}$$

$\beta$  is a regularization parameter,  $\partial\Omega$  is the regions boundaries of  $\Omega$ . Such problems is firstly introduced by Lions in [32].

There are two approaches to obtain the solution of the PDE-constrained optimization problems (6 - 8). The one is discretize-then-optimize and the other is optimize-then-discretize. By using the discretize-then-optimize approach and the  $Q_1$  finite element discretize in this paper, the following linear systems can be obtained:

$$\begin{pmatrix} 2\beta M & 0 & -M \\ 0 & M & K^T \\ -M & K & 0 \end{pmatrix} \begin{pmatrix} f \\ u \\ \lambda \end{pmatrix} = \begin{pmatrix} 0 \\ \tilde{b} \\ d \end{pmatrix},$$

where  $M, K \in \mathbb{R}^{n \times n}$  is the mass matrix and stiffness matrix (the discrete Laplacian) respectively. They are all SPD matrices.  $d \in \mathbb{R}^n$  is the terms coming from the boundary values,  $\tilde{b} \in \mathbb{R}^n$  is the discrete Galerkin projection of  $u_*$ ,  $\lambda$  is the Laplace operator vector.

As  $M$  is a symmetric matrix,  $\lambda = 2\beta f$  and the following linear systems of the form

$$\mathcal{A}z = \begin{pmatrix} M & \sqrt{2\beta}K \\ \sqrt{2\beta}K & -M \end{pmatrix} \begin{pmatrix} \mu \\ \sqrt{2\beta}f \end{pmatrix} = \begin{pmatrix} \tilde{b} \\ \sqrt{2\beta}d \end{pmatrix}, \quad (9)$$

can be obtained. we note that this system of linear equations have saddle point structure.

The eigenvalues distribution of the preconditioned matrix  $\widehat{M}^{-1}\mathcal{A}$  with  $\widehat{W} = 1.1W$  and  $V = \frac{10}{11}I < I$  are listed in Tables I - III, The symbol "-" denotes that the case is not exist.

From these Tables, we can find that the practical eigenvalues just fall in the interval theoretical eigenvalues, the theoretical bound of image are good agreement with the practical bound of image. To further illustrate this, The eigenvalues distribution of the preconditioned matrix  $\widehat{M}^{-1}\mathcal{A}$  is given in Fig. 1.

#### V. CONCLUSIONS

IN this paper, our focus is directed at the spectral property of the block  $2 \times 2$  linear systems, which frequently arise from saddle point problems and PDE-constrained optimization problems. Based on the Schur complement approximate approach, an inexact Uzawa preconditioner is introduced and the eigenvalues distribution of preconditioned matrix is discussed by the similarity transformation. The results of our numerical experiments utilizing test matrices from PDE-constrained optimization problems demonstrate that the theoretical bound for eigenvalues of the preconditioned matrix is good agreement with its practical bound.

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REFERENCES

[1] O. Axelsson and G. Lindskog, "On the eigenvalue distribution of a class of preconditioning methods," *Numerische Mathematik*, vol. 48, no. 5, pp. 479–498, 1986.

[2] O. Axelsson and A. Kucherov, "Real valued iterative methods for solving complex symmetric linear systems", *Numerical Linear Algebra with Applications*, vol. 7, no. 4, pp. 197–218, 2000.

[3] O. Axelsson and M. Neytcheva, "Eigenvalue estimates for preconditioned saddle point matrices", *Numerical Linear Algebra with Applications*, vol. 13, no. 4, pp. 339–360, 2006.

[4] V. E. Badalassi, H. D. Ceniceros and S. Banerjee, "Computation of multiphase systems with phase field models", *Journal of Computational Physics*, vol. 190, no. 2, pp. 371–397, 2003.

[5] Z.-Z. Bai, "Construction and analysis of structured preconditioners for block two-by-two matrices", *Journal of Shanghai University (English Edition)*, vol. 8, no. 4, pp. 397–405, 2004.

[6] Z.-Z. Bai, "Structured preconditioners for nonsingular matrices of block two-by-two structures", *Mathematics of Computation*, vol. 75, no. 254, pp. 791–815, 2006.

[7] Z.-Z. Bai, "Block preconditioners for elliptic PDE-constrained optimization problems", *Computing*, vol. 91, no. 4, pp. 379–395, 2011.

[8] Z.-Z. Bai, M. Benzi and F. Chen, "Modified HSS iteration methods for a class of complex symmetric linear systems", *Computing*, vol. 87, no. 3–4, pp. 93–111, 2011.

[9] Z.-Z. Bai, M. Benzi and F. Chen. "On preconditioned MHSS iteration methods for complex symmetric linear systems", *Numerical Algorithms*, vol. 56, no. 2, 297–317, 2011.

[10] Z.-Z. Bai, M. Benzi, F. Chen and Z.-Q. Wang, "Preconditioned MHSS iteration methods for a class of block two-by-two linear systems with applications to distributed control problems", *IMA Journal of Numerical Analysis*, vol. 33, no. 1, 343–369, 2013.

[11] M. Benzi and D. Bertaccini, "Block preconditioning of real-valued iterative algorithms for complex linear systems", *IMA Journal of Numerical Analysis*, vol. 28, no. 3, 598–618, 2008.

TABLE I: Bound of Eigenvalues of  $\widehat{M}^{-1}\mathcal{A}$  for  $\widehat{W} = 1.1W$ ,  $h = 2^{-4}$ .

$\beta$	$Re(\alpha)$	real eigenvalues		complex eigenvalues			
		Theoretical	Practical	Theoretical real	Practical real	Theoretical image	Practical image
$10^{-1}$	1/3	[0.7500, 1]	–	[0.8295, 0.9545]	[0.9618, 0.9544]	[-0.3061, 0.3061]	[-0.2980, 0.2980]
	1/4	[0.8000, 1]	–	[0.8545, 0.9545]	[0.9257, 0.9544]	[-0.3162, 0.3162]	[-0.2980, 0.2980]
	1/5	[0.8333, 1]	–	[0.8712, 0.9545]	[0.9312, 0.9545]	[-0.3227, 0.3227]	[-0.2981, 0.2981]
	1/6	[0.8571, 1]	–	[0.8831, 0.9545]	[0.9349, 0.9545]	[-0.3273, 0.3273]	[-0.2981, 0.2981]
$10^{-2}$	1/3	[0.7500, 1]	–	[0.8295, 0.9545]	[0.8612, 0.9541]	[-0.3061, 0.3061]	[-0.2980, 0.2980]
	1/4	[0.8000, 1]	–	[0.8545, 0.9545]	[0.8811, 0.9542]	[-0.3161, 0.3161]	[-0.2980, 0.2980]
	1/5	[0.8333, 1]	–	[0.8712, 0.9545]	[0.8940, 0.9543]	[-0.3227, 0.3227]	[-0.2980, 0.2980]
	1/6	[0.8571, 1]	–	[0.8831, 0.9545]	[0.9030, 0.9543]	[-0.3273, 0.3273]	[-0.2980, 0.2980]

TABLE II: Bound of Eigenvalues of  $\widehat{M}^{-1}\mathcal{A}$  for  $\widehat{W} = 1.1W$ ,  $h = 2^{-5}$ .

$\beta$	$Re(\alpha)$	real eigenvalues		complex eigenvalues			
		Theoretical	Practical	Theoretical real	Practical real	Theoretical image	Practical image
$10^{-1}$	1/3	[0.7500, 1]	–	[0.8295, 0.9545]	[0.9167, 0.9545]	[-0.3062, 0.3062]	[-0.2981, 0.2981]
	1/4	[0.8000, 1]	–	[0.8545, 0.9545]	[0.9256, 0.9545]	[-0.3162, 0.3162]	[-0.2981, 0.2981]
	1/5	[0.8333, 1]	–	[0.8712, 0.9545]	[0.9311, 0.9545]	[-0.3227, 0.3227]	[-0.2981, 0.2981]
	1/6	[0.8571, 1]	–	[0.8831, 0.9545]	[0.9349, 0.9545]	[-0.3273, 0.3273]	[-0.2981, 0.2981]
$10^{-2}$	1/3	[0.7500, 1]	–	[0.8295, 0.9545]	[0.8610, 0.9544]	[-0.3062, 0.3062]	[-0.2980, 0.2980]
	1/4	[0.8000, 1]	–	[0.8545, 0.9545]	[0.8810, 0.9545]	[-0.3162, 0.3162]	[-0.2981, 0.2981]
	1/5	[0.8333, 1]	–	[0.8712, 0.9545]	[0.8939, 0.9545]	[-0.3227, 0.3227]	[-0.2981, 0.2981]
	1/6	[0.8571, 1]	–	[0.8831, 0.9545]	[0.9030, 0.9545]	[-0.3273, 0.3273]	[-0.2981, 0.2981]

TABLE III: Bound of Eigenvalues of  $\widehat{M}^{-1}\mathcal{A}$  for  $\widehat{W} = 1.1W$ ,  $h = 2^{-6}$ .

$\beta$	$Re(\alpha)$	real eigenvalues		complex eigenvalues			
		Theoretical	Practical	Theoretical real	Practical real	Theoretical image	Practical image
$10^{-1}$	1/2	[0.6667, 1]	–	[0.7879, 0.9545]	[0.8998, 0.9545]	[-0.2887, 0.2887]	[-0.2981, 0.2981]
	1/3	[0.7500, 1]	–	[0.8295, 0.9545]	[0.9167, 0.9545]	[-0.3062, 0.3062]	[-0.2981, 0.2981]
	1/4	[0.8000, 1]	–	[0.8545, 0.9545]	[0.9256, 0.9545]	[-0.3162, 0.3162]	[-0.2981, 0.2981]
	1/5	[0.8333, 1]	–	[0.8712, 0.9545]	[0.9311, 0.9545]	[-0.3227, 0.3227]	[-0.2981, 0.2981]
	1/6	[0.8571, 1]	–	[0.8831, 0.9545]	[0.9349, 0.9545]	[-0.3273, 0.3273]	[-0.2981, 0.2981]
$10^{-2}$	1/2	[0.6667, 1]	–	[0.7879, 0.9545]	[0.8262, 0.9535]	[-0.2887, 0.2887]	[-0.2981, 0.2981]
	1/3	[0.7500, 1]	–	[0.8295, 0.9545]	[0.8610, 0.9545]	[-0.3062, 0.3062]	[-0.2981, 0.2981]
	1/4	[0.8000, 1]	–	[0.8545, 0.9545]	[0.8809, 0.9545]	[-0.3162, 0.3162]	[-0.2981, 0.2981]
	1/5	[0.8333, 1]	–	[0.8712, 0.9545]	[0.8939, 0.9545]	[-0.3227, 0.3227]	[-0.2981, 0.2981]
	1/6	[0.8571, 1]	–	[0.8831, 0.9545]	[0.9029, 0.9545]	[-0.3273, 0.3273]	[-0.2981, 0.2981]

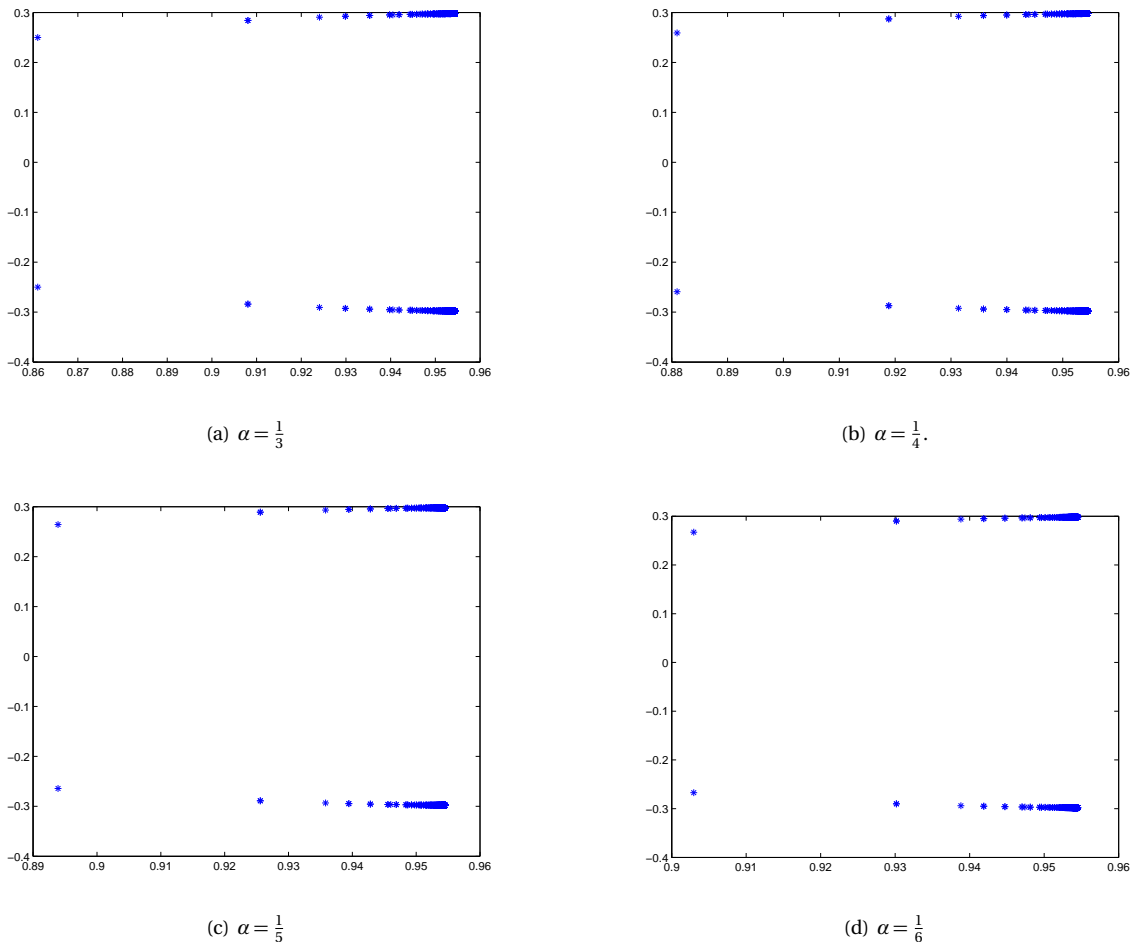


Fig. 1: Eigenvalues distribution of preconditioned matrix  $\widehat{M}^{-1}\mathcal{A}$  ( $\beta = 10^{-2}, h = 2^{-5}$ ).

[12] M. Benzi, G. H. Golub and J. Liesen, “Numerical solution of saddle point problems”, *Acta Numerica*, vol. 14, 1–137, 2005.

[13] M. Benzi and V. Simoncini, “On the eigenvalues of a class of saddle point matrices”, *Numerische Mathematik*, vol. 103, no. 2, 173–196, 2006.

[14] L. Bergamaschi, “On eigenvalue distribution of constraint preconditioned symmetric saddle point matrices”, *Numerical Linear Algebra with Applications*, vol. 19, no. 4, 754–772, 2012.

[15] L. Bergamaschi and Á. Martínez, “RMCP: relaxed mixed constraint preconditioners for saddle point linear systems arising in geomechanics”, *Computer Methods in Applied Mechanics and Engineering*, vol. 221–222, pp. 54–62, 2012.

[16] A. Berti and I. Bochicchio, “A mathematical model for phase separation: A generalized Cahn-Hilliard equation”, *Mathematical Methods in the Applied Sciences*, vol. 34, no. 10, pp. 1193–1201, 2011.

[17] J. H. Bramble, J. E. Pasciak, E. Joseph, et al, “Analysis of the inexact Uzawa algorithm for saddle point problems”, *SIAM Journal on Numerical Analysis*, vol. 34, no. 3, pp. 1072–1092, 1997.

[18] H. Dai, “Completing a symmetric  $2 \times 2$  block matrix and its inverse”, *Linear Algebra and Its Applications*, vol. 235, pp. 235–245, 1996.

[19] E. de Sturler, J. Liesen, “Block-diagonal and constraint preconditioners for nonsymmetric indefinite linear systems. Part I: Theory”, *SIAM Journal on Scientific Computing*, vol. 26, no. 5, pp. 1598–1619, 2005.

[20] J. Liesen and B. N. Parlett, “On nonsymmetric saddle point matrices that allow conjugate gradient iterations”, *Numerische Mathematik*, vol. 108, no. 4, pp. 605–624, 2008.

[21] K. Omid, V. L. Andrei, K. Kristian, “A comparative study of preconditioning techniques for large sparse systems arising infinite element limit analysis”, *IAENG International Journal of Applied Mathematics*, vol. 43, no.4, pp. 195–203, 2013

[22] J. B. Erway, R. F. Marcia, J. Tyson, “Generalized diagonal pivoting methods for tridiagonal systems without interchanges”, *IAENG International Journal of Applied Mathematics*, vol. 40, no. 4, pp. 269–275, 2010.

[23] M. Keyanpour, A. Mahmoudi, “A hybrid method for solving optimal control problems”, *IAENG International Journal of Applied Mathematics*, vol. 42, no. 2, pp. 80–86, 2012.

[24] Y. Notay, “A new analysis of block preconditioners for saddle point problems”, *SIAM journal on Matrix Analysis and Applications*, vol. 35, no. 1, pp. 143–173, 2014.

[25] T. Rees, H. S. Dollar and A. J. Wathen, “Optimal solvers for PDE-constrained optimization”, *SIAM Journal on Scientific Computing*, vol. 32, no. 1, pp. 271–298, 2010.

[26] M. ur Rehman, C. Vuik, G. Segal “Preconditioners for steady incompressible Navier-Stokes problem”, *International Journal of Applied Mathematics*, vol. 38, no. 4, pp. IJAM\_38\_4\_09, 2008.

[27] S.-Q. Shen, T.-Z. Huang and G.-H. Cheng, “A condition for the non-symmetric saddle point matrix being diagonalizable and having real and positive eigenvalues”, *Journal of Computational and Applied Mathematics*, vol. 220, no. 1, pp. 8–12, 2008.

[28] S.-Q. Shen, T.-Z. Huang and J. Yu, “Eigenvalue estimates for preconditioned nonsymmetric saddle point matrices”, *SIAM Journal on Matrix Analysis and Applications*, vol. 31, no. 5, pp. 2453–2476, 2010

[29] S.-Q. Shen, L. Jian, W.-D. Bao and T.-Z. Huang, “On the eigenvalue distribution of preconditioned nonsymmetric saddle point matrices”, *Numerical Linear Algebra with Applications*, vol. 21, no. 4, pp. 557–568, 2014.

[30] V. Simoncini, “Block triangular preconditioners for symmetric saddle-point problems”, *Applied Numerical Mathematics*, vol. 49, no. 1, pp. 63–80, 2004.

[31] G.-F. Zhang and Z. Zheng, “Block-symmetric and block-lower-triangular preconditioners for PDE-constrained optimization problems”, *Journal of Computational Mathematics*, vol. 31, no. 4, pp. 370–381, 2013.

[32] J. L. Lions, *Optimal control of systems governed by partial differential equations*. Springer Verlag, 1971.