

A conjugate gradient-based algorithm for large-scale quadratic programming problem with one quadratic constraint

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Abstract In this paper, we consider the nonconvex quadratically constrained quadratic programming (QCQP) with one quadratic constraint. By employing the conjugate gradient method, an efficient algorithm is proposed to solve QCQP that exploits the sparsity of the involved matrices and solves the problem via solving a sequence of positive definite system of linear equations after identifying suitable generalized eigenvalues. Some numerical experiments are given to show the effectiveness of the proposed method and to compare it with some recent algorithms in the literature.

Keywords QCQP, Conjugate gradient algorithm, Generalized eigenvalue problem.

1 Introduction

We consider the following quadratically constrained quadratic programming (QCQP)

$$\begin{aligned} \min \quad & q(x) := x^T A x + 2a^T x \\ & g(x) := x^T B x + 2b^T x + \beta \leq 0, \end{aligned} \quad (\text{QCQP})$$

where $A, B \in \mathbb{R}^{n \times n}$ are symmetric matrices with no definiteness assumed, $a, b \in \mathbb{R}^n$ and $\beta \in \mathbb{R}$. When $B = I$, $b = 0$ and $\beta < 0$, QCQP reduces to the classical trust-region subproblem (TRS), which arises in regularization or trust-region methods for unconstrained optimization [5,24]. Despite being nonconvex, numerous efficient algorithms have been developed to solve TRS [1,6,8,9,18]. The existing algorithms for TRS can be classified into two categories; approximate methods and accurate methods. The Steihaug-Toint algorithm is a well-known approximate method that

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exploits the preconditioned conjugate gradient iterations for unconstrained minimization of $q(x)$ to obtain an approximate solution to large-scale instances of TRS [20, 22]. Precisely, the method follows a piecewise linear path connecting the conjugate gradient iterates for solving the system $Ax = -a$, which either finds an interior solution of TRS or terminates with a point on the boundary which does not allow the accuracy of the constrained solution to be specified. To overcome the lack of accuracy of Steihaug-Toint algorithm, Gould et al. in [8] proposed the generalized Lanczos trust-region method which minimizes the problem on an expanding sequence of subspaces generated by Lanczos vectors. The classical algorithm [15] by Moré and Sorensen is an accurate method for TRS, which at each iteration makes use of the Cholesky factorization to solve a positive definite linear system and hence is not proper for large-scale instances. A number of algorithms designed for large-scale TRS reformulate the problem as a parameterized eigenvalue problem [6, 18, 19]. More recently, it has been shown that TRS can be solved by one generalized eigenvalue problem [1].

The QCQP is a natural generalization of TRS and is important in scaled trust-region methods for nonlinear optimization, allowing a possible indefinite scaling matrix. It also has applications in double well potential problems [7] and compressed sensing for geological data [11]. In recent years, QCQP has received much attention in the literature and various methods have been developed to solve it [3, 13, 16, 17, 21, 23]. In [16], Moré gives a characterization of the global minimizer of QCQP and describes an algorithm for the solution of QCQP which extends the one for TRS [15]. A connection between the solution methods for QCQP and semidefinite programming (SDP) is established in [23]. However, the SDP approach is not practical for large-scale problems. Recently, it has been shown that when the quadratic forms are simultaneously diagonalizable, QCQP has a second order cone programming (SOCP) reformulation which is significantly more tractable than a semidefinite problem [3]. In [13], the authors further showed that QCQP with an optimal value bounded from below is SOCP representable, which extends the results in [3]. The QCQP with the two-sided constraint has been studied in [17]. In particular, it has been shown that QCQP can be transformed into a parameterized generalized eigenvalue problem [17]. Salahi and Taati [21] also derived a diagonalization-based algorithm under the simultaneous diagonalizable condition of the quadratic forms. The method is proper for small and medium-scale instances since it needs matrix factorization. Recently, Adachi and Nakatsukasa developed an algorithm for QCQP that requires finding just one eigenpair of a generalized eigenvalue problem [2], extending the one for TRS [1]. However, due to the requirement of constructing explicit form of the Hessian matrices, when the involved matrices are not highly sparse, the method is not efficient for large-scale problems. Most recently, in [12], the authors have derived a novel convex quadratic reformulation for QCQP and established that the optimal solution of QCQP can be recovered from the optimal solution of the new reformulation. They also developed two efficient algorithms to solve the new reformulation.

In the present paper, we propose a conjugate gradient-based algorithm for QCQP which applies the conjugate gradient method to solve a sequence of positive definite system of linear equations, and hence is efficient for large sparse instances of QCQP. It is worth noting that although the method of [16] and ours follow the same framework to solve the problem in the case where the optimal Lagrangian Hessian matrix is positive definite, there are some differences in our approach.

Firstly, in [16], no specific algorithm is proposed to solve the so-called secular equation while here we propose an efficient algorithm to solve it. Secondly, our approach first verifies hard case (case 2) and if it is detected, the optimal solution of QCQP is computed via solving a positive definite system. We also emphasize that our approach for verifying hard case 2 is different from the one presented in [17].

The rest of the paper is organized as follows. In Section 2, we review some known facts related to QCQP. A conjugate-gradient based algorithm is introduced in Section 3. Finally, in Section 4, we give some numerical results to show the effectiveness of the proposed method comparing with the algorithms from [2] and [12].

Notations: Throughout this paper, for two symmetric matrices A and B , $\lambda_{\min}(A, B)$ denotes the smallest generalized eigenvalue of pencil (A, B) , $A \succ 0$ ($A \succeq 0$) denotes A is positive definite (positive semidefinite), A^\dagger denotes the Moore-Penrose generalized inverse of A , $\text{Range}(A)$ and $\text{Null}(A)$ denote its Range and Null spaces, respectively. Finally, for an interval I , $\text{int}(I)$ stands for its interior.

2 Preliminaries: optimality, easy and hard cases

In this section, we state some results related to the QCQP that are useful in the next section. We start by considering the following assumptions.

Assumption 1. QCQP satisfies the Slater's condition, i.e., there exists \hat{x} with $g(\hat{x}) < 0$.

Assumption 2. There exists $\hat{\lambda} \geq 0$ such that $A + \hat{\lambda}B \succ 0$.

When Assumption 1 is violated, QCQP reduces to an unconstrained minimization problem and Assumption 2 ensures that QCQP has an optimal solution [2]. The following theorem gives a set of necessary and sufficient conditions for the global optimal solution of QCQP under Assumption 1.

Theorem 1 ([16]) *Suppose that QCQP satisfies Assumption 1. Then x^* is a global optimal solution if and only if there exists $\lambda^* \geq 0$ such that*

$$(A + \lambda^*B)x^* = -(a + \lambda^*b), \quad (1)$$

$$g(x^*) \leq 0, \quad (2)$$

$$\lambda^*g(x^*) = 0, \quad (3)$$

$$(A + \lambda^*B) \succeq 0. \quad (4)$$

□

An optimal solution of QCQP belongs to one of the following two types: an interior solution with $g(x^*) < 0$ or a boundary solution with $g(x^*) = 0$. The following lemma states the case where QCQP has no boundary solution.

Lemma 1 *The QCQP has no optimal solution on the boundary of the feasible region if and only if $A \succ 0$ and $g(-A^{-1}a) < 0$.*

Proof Let x^* be the optimal solution of QCQP. If $A \not\succeq 0$, then from Theorem 1, $g(x^*) = 0$ and hence the optimal solution is on the boundary of the feasible

region. Now suppose that A is positive semidefinite (singular) and $g(x^*) < 0$. Let $v \in \text{Null}(A)$ and consider the following quadratic equation of variable α :

$$g(x^* + \alpha v) = (x^* + \alpha v)^T B(x^* + \alpha v) + 2b^T(x^* + \alpha v) + \beta = 0.$$

This equation has a root since $v^T Bv > 0$ and $g(x^*) < 0$. To show $v^T Bv > 0$, recall that, by Assumption 2, there exists $\hat{\lambda} \geq 0$ with $A + \hat{\lambda}B \succ 0$. This implies that $v^T Av + \hat{\lambda}v^T Bv > 0$. Since $v^T Av = 0$, then $v^T Bv > 0$. The discussion above proves that in the case where A is positive semidefinite (singular), QCQP has a solution on the boundary. The only case that must be considered is the case where A is positive definite. In this case, $x^* = -A^{-1}a$ is the unique unconstrained minimizer of $g(x)$. Hence, QCQP has no solution with $g(x^*) = 0$ if and only if $g(-A^{-1}a) < 0$. \square

In view of Lemma 1, unless $A \succ 0$ and $g(-A^{-1}a) < 0$, QCQP has a boundary solution. Hence, from now on, we focus on the boundary solutions since an interior solution that can be obtained by solving the linear system $Ax = -a$.

By Assumption 2, A and B are simultaneously diagonalizable [14], i. e., there exists an invertible matrix Q and diagonal matrices $D = \text{diag}(d_1, \dots, d_n)$ and $E = \text{diag}(e_1, \dots, e_n)$ such that $Q^T A Q = D$ and $Q^T B Q = E$. It is easy to see that $A + \lambda B \succeq 0$ if and only if $\underline{\lambda} \leq \lambda \leq \bar{\lambda}$ where

$$\underline{\lambda} = \max\left\{-\frac{d_i}{e_i} \mid e_i > 0\right\}, \quad \bar{\lambda} = \min\left\{-\frac{d_i}{e_i} \mid e_i < 0\right\}.$$

If $A \succ 0$, $\underline{\lambda} < 0$ else $\underline{\lambda} \geq 0$. Let I be the smallest interval containing all nonnegative λ satisfying the optimality conditions (1) and (4). It follows from Theorem 1 that the interior of I , $\text{int}(I) = (\max\{0, \underline{\lambda}\}, \bar{\lambda})$. The interval I contains $\bar{\lambda}$ as the right endpoint if $(a + \bar{\lambda}b) \in \text{Range}(A + \bar{\lambda}B)$ and it contains $\underline{\lambda}$ as the left endpoint if $\underline{\lambda} \geq 0$ and $(a + \underline{\lambda}b) \in \text{Range}(A + \underline{\lambda}B)$. For any $\lambda \in (\underline{\lambda}, \bar{\lambda})$, define

$$\phi(\lambda) := x(\lambda)^T Bx(\lambda) + 2b^T x(\lambda) + \beta,$$

where $x(\lambda) = -(A + \lambda B)^{-1}(a + \lambda b)$. The function $\phi(\lambda)$ has the following properties.

Lemma 2 ([16]) $\phi(\lambda)$ is either constant or strictly decreasing on $(\underline{\lambda}, \bar{\lambda})$. $\phi(\lambda)$ is constant if and only if

$$\begin{bmatrix} a \\ b \end{bmatrix} \in \text{Range} \begin{bmatrix} A \\ B \end{bmatrix}. \quad (5)$$

Proposition 1 ([2, 16]) Suppose that $\bar{\lambda} = +\infty$. Then $\lim_{\lambda \rightarrow +\infty} \phi(\lambda) < 0$.

The QCQP similar to TRS is classified into easy case and hard case (case 1 and 2) instances. The characterization of the easy and hard cases of the QCQP with the two-sided constraint is given in [17]. Here we adapt the characterization for the QCQP based on the requirement $\lambda^* \geq 0$ where λ^* denotes the optimal Lagrange multiplier. We have to consider separately the cases where A is positive definite and A is not positive definite as follows:

– **A is positive definite.**

1. The easy case occurs if one of the following holds:

- (i) $\bar{\lambda}$ is infinite.
 - (ii) $\bar{\lambda}$ is finite and $a + \bar{\lambda}b \notin \text{Range}(A + \bar{\lambda}B)$. This implies that $\lambda^* \in [0, \bar{\lambda})$.
2. The hard case 1 occurs if the following holds:
 - (i) $\bar{\lambda}$ is finite and $a + \bar{\lambda}b \in \text{Range}(A + \bar{\lambda}B)$ and $\lambda^* \in [0, \bar{\lambda})$.
 3. The hard case 2 occurs if the following holds:
 - (iii) $\bar{\lambda}$ is finite and $a + \bar{\lambda}b \in \text{Range}(A + \bar{\lambda}B)$ and $\lambda^* = \bar{\lambda}$.
- **A is not positive definite.**
1. The easy case occurs if one of the following three cases holds:
 - (i) Both $\underline{\lambda}$ and $\bar{\lambda}$ are finite, $a + \underline{\lambda}b \notin \text{Range}(A + \underline{\lambda}B)$ and $a + \bar{\lambda}b \notin \text{Range}(A + \bar{\lambda}B)$. This implies that $\lambda^* \in (\underline{\lambda}, \bar{\lambda})$.
 - (ii) Only $\underline{\lambda}$ is finite and $a + \underline{\lambda}b \notin \text{Range}(A + \underline{\lambda}B)$. This implies that $\lambda^* \in (\underline{\lambda}, \infty)$.
 - (iii) Only $\bar{\lambda}$ is finite and $a + \bar{\lambda}b \notin \text{Range}(A + \bar{\lambda}B)$. This implies that $\lambda^* \in (-\infty, \bar{\lambda})$.
 2. The hard case 1 occurs if one of the following three cases holds:
 - (i) Both $\underline{\lambda}$ and $\bar{\lambda}$ are finite and $a + \underline{\lambda}b \in \text{Range}(A + \underline{\lambda}B)$ or $a + \bar{\lambda}b \in \text{Range}(A + \bar{\lambda}B)$ and $\lambda^* \in (\underline{\lambda}, \bar{\lambda})$.
 - (ii) Only $\underline{\lambda}$ is finite and $a + \underline{\lambda}b \in \text{Range}(A + \underline{\lambda}B)$ and $\lambda^* \in (\underline{\lambda}, \infty)$.
 - (iii) Only $\bar{\lambda}$ is finite and $a + \bar{\lambda}b \in \text{Range}(A + \bar{\lambda}B)$ and $\lambda^* \in (-\infty, \bar{\lambda})$.
 3. The hard case 2 occurs if one of the following holds:
 - (i) Both $\underline{\lambda}$ and $\bar{\lambda}$ are finite and $a + \underline{\lambda}b \in \text{Range}(A + \underline{\lambda}B)$ and $\lambda^* = \underline{\lambda}$ or $a + \bar{\lambda}b \in \text{Range}(A + \bar{\lambda}B)$ and $\lambda^* = \bar{\lambda}$.
 - (ii) Only $\underline{\lambda}$ is finite and $a + \underline{\lambda}b \in \text{Range}(A + \underline{\lambda}B)$ and $\lambda^* = \underline{\lambda}$.
 - (iii) Only $\bar{\lambda}$ is finite and $a + \bar{\lambda}b \in \text{Range}(A + \bar{\lambda}B)$ and $\lambda^* = \bar{\lambda}$.

From Lemma 2 and Proposition 1, we see that in the easy case and hard case 1, λ^* is the unique solution of equation $\phi(\lambda) = 0$ in the interval $(\max\{0, \underline{\lambda}\}, \bar{\lambda})$. Hard case 2 corresponds to the case where equation $\phi(\lambda) = 0$ has no solution in $(\max\{0, \underline{\lambda}\}, \bar{\lambda})$.

3 A conjugate gradient-based algorithm

In this section, we assume that a value of $\hat{\lambda}$ such that $A + \hat{\lambda}B \succ 0$ is known. By Lemma 1, excluding the case where A is positive definite and $g(-A^{-1}a) < 0$, solving QCQP is equivalent to find a nonnegative $\lambda^* \in [\max\{0, \underline{\lambda}\}, \bar{\lambda}]$ such that $\phi(\lambda^*) = 0$. Note that except the case where QCQP is a hard case 2 instance, the nonlinear equation $\phi(\lambda) = 0$ has a unique root in interval $(\max\{0, \underline{\lambda}\}, \bar{\lambda})$. According to this fact, we propose a conjugate gradient-based algorithm for QCQP which first checks for hard case 2 and if this is the case, a global optimal solution of QCQP is obtained via solving a positive definite system of linear equations, otherwise, the global solution of QCQP is computed by finding the root of equation $\phi(\lambda) = 0$ in $(\max\{0, \underline{\lambda}\}, \bar{\lambda})$. We use the value of $\phi(\hat{\lambda})$ to form the algorithm. We consider the following three cases:

1. **Case 1.** $\phi(\hat{\lambda}) = 0$.
In this case, obviously $(\hat{\lambda}, x(\hat{\lambda}))$ satisfies the optimality conditions (1) to (4) and hence $x(\hat{\lambda})$ is the unique optimal solution of QCQP.
2. **Case 2.** $\phi(\hat{\lambda}) > 0$.
In this case, by Lemma 2, $\lambda^* \in (\hat{\lambda}, \bar{\lambda}]$. Now we consider the following two possible subcases:

- (a) $\bar{\lambda}$ is infinite. In this case, from Proposition 1, equation $\phi(\lambda) = 0$ has a unique root in $(\hat{\lambda}, \bar{\lambda})$.
- (b) $\bar{\lambda}$ is finite. In this case, either QCQP is a hard case 2 instance ($\lambda^* = \bar{\lambda}$) or equation $\phi(\lambda) = 0$ has a unique root in $(\hat{\lambda}, \bar{\lambda})$.
3. **Case 3.** $\phi(\hat{\lambda}) < 0$.
 In this case, by Lemma 2, $\lambda^* \in [\max\{0, \underline{\lambda}\}, \hat{\lambda})$. Now we consider the following two possible subcases:
- (a) If $\underline{\lambda} < 0$, then $A > 0$. Set $x^* = -A^{-1}a$. If $g(x^*) \leq 0$, then x^* with $\lambda^* = 0$ is the optimal solution of QCQP. Otherwise, equation $\phi(\lambda) = 0$ has a unique root in $(0, \hat{\lambda})$.
- (b) If $\underline{\lambda} \geq 0$, either QCQP is a hard case 2 instance ($\lambda^* = \underline{\lambda}$) or equation $\phi(\lambda) = 0$ has a unique root in $(\underline{\lambda}, \hat{\lambda})$.

To the best of our knowledge, there is no algorithm in the literature to compute $\underline{\lambda}$ and $\bar{\lambda}$ for general A and B when the value of $\hat{\lambda}$ is not known. However, when the value of $\hat{\lambda}$ is available, $\underline{\lambda}$ and $\bar{\lambda}$ can be efficiently computed via finding some generalized eigenvalues of a matrix pencil [12, 17]. Precisely, $A + \lambda B \succeq 0$ if and only if $\underline{\lambda} \leq \lambda \leq \bar{\lambda}$ where $\underline{\lambda} = \lambda_1 + \hat{\lambda}$, $\bar{\lambda} = \lambda_2 + \hat{\lambda}$,

$$\lambda_1 = \begin{cases} \frac{1}{\lambda_{\min}(-B, A + \hat{\lambda}B)} & \text{if } \lambda_{\min}(-B, A + \hat{\lambda}B) < 0, \\ -\infty & \text{otherwise,} \end{cases}$$

and

$$\lambda_2 = \begin{cases} \frac{1}{\lambda_{\min}(B, A + \hat{\lambda}B)} & \text{if } \lambda_{\min}(B, A + \hat{\lambda}B) < 0, \\ \infty & \text{otherwise.} \end{cases}$$

It is worth noting that, when $\hat{\lambda}$ is given, we only need to compute one extreme eigenvalue to determine the initial interval containing the optimal Lagrange multiplier, i.e., only one of $\underline{\lambda}$ and $\bar{\lambda}$.

3.1 Verifying hard case 2

In this subsection, we discuss how one can detect hard case 2 if it is the case. In [17], Pong and Wolkowicz proposed an algorithm based on minimum generalized eigenvalue of a parameterized matrix pencil to solve QCQP with the two-sided constraint that first carries out a preprocessing technique to recognize hard case 2, see Section 3.1.1 of [17] for more details. According to their result, when $\underline{\lambda} \in I$ and $\lambda^* \in [\underline{\lambda}, \hat{\lambda})$, QCQP is hard case 2 if and only if $g(x(\underline{\lambda})) \leq 0$ where $x(\underline{\lambda}) = -(A + \underline{\lambda}B)^\dagger(a + \underline{\lambda}b)$. Similarly, when $\bar{\lambda} \in I$ and $\lambda^* \in (\hat{\lambda}, \bar{\lambda}]$, QCQP is hard case 2 if and only if $g(x(\bar{\lambda})) \geq 0$ where $x(\bar{\lambda}) = -(A + \bar{\lambda}B)^\dagger(a + \bar{\lambda}b)$. Unfortunately, in general these assertions are not true, QCQP may be hard case 2 but $g(x(\underline{\lambda})) > 0$ or $g(x(\bar{\lambda})) < 0$. A problem of this type is given in the following example.

Example 1 Consider a QCQP with

$$A = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 2 & 0 \\ 0 & -1 \end{bmatrix}, a = \begin{bmatrix} -25 \\ -\frac{33}{2} \end{bmatrix}, b = \begin{bmatrix} 50 \\ 25 \end{bmatrix}, \beta = 0,$$

and set $\hat{\lambda} = \frac{3}{4}$. It is easy to see that $\underline{\lambda} = \frac{1}{2}$, $\bar{\lambda} = 1$, $\phi(\hat{\lambda}) < 0$ and $(a + \underline{\lambda}b) \in \text{Range}(A + \underline{\lambda}B)$, and so $\lambda^* \in [\underline{\lambda}, \hat{\lambda})$. This problem is hard case 2 since $x^* = [-25 + \sqrt{457}, 8]^T$ with $\lambda^* = \underline{\lambda}$ satisfy the optimality conditions

$$\begin{aligned}(A + \underline{\lambda}B)x^* &= -(a + \underline{\lambda}b), \\ g(x^*) &= 0.\end{aligned}$$

On the other hand, we have $x(\underline{\lambda}) = [0, 8]^T$ and $g(x(\underline{\lambda})) = 336 > 0$.

In what follows, we fill this gap and describe an approach to recognize hard case 2. We use the following result.

Proposition 2 ([16]) *If $\bar{\lambda}$ is finite, then $v^T Bv < 0$ for all nonzero $v \in \text{Null}(A + \bar{\lambda}B)$. If $\underline{\lambda}$ is finite, then $v^T Bv > 0$ for all nonzero $v \in \text{Null}(A + \underline{\lambda}B)$.*

Consider the following two cases.

Case 1: $\bar{\lambda} \in I$ and $\lambda^* \in (\hat{\lambda}, \bar{\lambda}]$.

First notice that since $\bar{\lambda} \in I$, then $(a + \bar{\lambda}b) \in \text{Range}(A + \bar{\lambda}B)$. Hence, system

$$(A + \bar{\lambda}B)x = -(a + \bar{\lambda}b), \quad (6)$$

is consistent. Assume that the set $\{v_1, v_2, \dots, v_r\}$ is an orthonormal basis of $\text{Null}(A + \bar{\lambda}B)$. Set $Z = [v_1, v_2, \dots, v_r]$, then any solution of system (6) has the form $x = x(\bar{\lambda}) + Zy$ where $x(\bar{\lambda}) = -(A + \bar{\lambda}B)^\dagger(a + \bar{\lambda}b)$ and $y \in \mathbb{R}^r$. Now consider the following maximization problem:

$$p^* := \max_{y \in \mathbb{R}^r} g(x(\bar{\lambda}) + Zy) = y^T Z^T BZy + 2y^T Z^T (Bx(\bar{\lambda}) + b) + g(x(\bar{\lambda})). \quad (7)$$

By Proposition 2, $Z^T BZ \prec 0$ and hence the optimal solution of (7), y^* , is the unique solution of the positive definite system

$$-(Z^T BZ)y^* = Z^T (Bx(\bar{\lambda}) + b), \quad (8)$$

and $p^* = g(x(\bar{\lambda}) + Zy^*)$. In the sequel, we show that $\lambda^* = \bar{\lambda}$ if and only if $p^* \geq 0$. To see this, suppose that $p^* \geq 0$. Set $x^* = x(\bar{\lambda}) + Zy^*$. Next consider the following quadratic equation of variable α :

$$v^T Bv\alpha^2 + 2\alpha v^T (Bx^* + b) + p^* = 0,$$

where $v \in \text{Null}(A + \bar{\lambda}B)$. Due to the facts that $v^T Bv < 0$ and $p^* \geq 0$, the above equation has a root α . Now it is easy to see that $x^* := x^* + \alpha v$ with $\lambda^* = \bar{\lambda}$ satisfies the optimality conditions of QCQP:

$$\begin{aligned}(A + \bar{\lambda}B)x^* &= -(a + \bar{\lambda}b), \\ g(x^*) &= 0.\end{aligned}$$

Next suppose that $\lambda^* = \bar{\lambda}$ and x^* is a global optimal solution of QCQP. Since $\bar{\lambda} > 0$, it follows from optimality conditions that $g(x^*) = 0$ and thus $p^* \geq 0$.

Case 2: $\underline{\lambda} \in I$ and $\lambda^* \in [\underline{\lambda}, \hat{\lambda})$.

This is similar to Case 1. First notice that since $\underline{\lambda} \in I$, then $(a + \underline{\lambda}b) \in \text{Range}(A + \underline{\lambda}B)$. Hence, system

$$(A + \underline{\lambda}B)x = -(a + \underline{\lambda}b), \quad (9)$$

is consistent. Assume that the set $\{v_1, v_2, \dots, v_r\}$ is an orthonormal basis of $\text{Null}(A + \underline{\lambda}B)$. Set $Z = [v_1, v_2, \dots, v_r]$, then any solution of system (9) has the form $x = x(\underline{\lambda}) + Zy$ where $x(\underline{\lambda}) = -(A + \underline{\lambda}B)^\dagger(a + \underline{\lambda}b)$ and $y \in \mathbb{R}^r$. Now consider the following minimization problem:

$$p^* := \min_{y \in \mathbb{R}^r} g(x(\underline{\lambda}) + Zy) = y^T Z^T B Z y + 2y^T Z^T (Bx(\underline{\lambda}) + b) + g(x(\underline{\lambda})). \quad (10)$$

By Proposition 2, $Z^T B Z \succ 0$ and hence the optimal solution of (10), y^* , is the unique solution of the positive definite system

$$(Z^T B Z)y^* = -Z^T (Bx(\underline{\lambda}) + b), \quad (11)$$

and $p^* = g(x(\underline{\lambda}) + Zy^*)$. In the sequel, we show that $\lambda^* = \underline{\lambda}$ if and only if $p^* \leq 0$. To see this, suppose that $p^* \leq 0$. Set $x^* = x(\underline{\lambda}) + Zy^*$. Next consider the following quadratic equation of variable α :

$$v^T B v \alpha^2 + 2\alpha v^T (Bx^* + b) + p^* = 0,$$

where $v \in \text{Null}(A + \underline{\lambda}B)$. Due to the facts that $v^T B v > 0$ and $p^* \leq 0$, the above equation has a root α . Now it is easy to see that $x^* := x^* + \alpha v$ with $\lambda^* = \underline{\lambda}$ satisfies the optimality conditions of QCQP:

$$\begin{aligned} (A + \underline{\lambda}B)x^* &= -(a + \underline{\lambda}b), \\ g(x^*) &= 0. \end{aligned}$$

Next suppose that $\lambda^* = \underline{\lambda}$ and x^* is a global optimal solution of QCQP. Since $\bar{\lambda} > 0$, it follows from optimality conditions that $g(x^*) = 0$ and thus $p^* \leq 0$.

Example 2 Consider the same problem in Example 1. We have $\underline{\lambda} \in I$ and $\lambda^* \in [\underline{\lambda}, \hat{\lambda}]$. Moreover, $Z = [1, 0]^T$ is an orthonormal basis of $\text{Null}(A + \underline{\lambda}B)$ and $x(\underline{\lambda}) = [0, 8]^T$. It is easy to see that the optimal solution of problem (10), $y^* = -25$ and so $p^* = -914 < 0$. Therefore, QCQP is a hard case 2 instance and $x^* = [-25 + \sqrt{457}, 8]^T$ with $\lambda^* = \underline{\lambda}$ satisfy the optimality conditions.

3.2 Solving the nonlinear equation $\phi(\lambda) = 0$

When QCQP is not hard case 2, λ^* is the unique solution of the equation $\phi(\lambda) = 0$ on the underlying interval containing the optimal Lagrange multiplier. If B is positive semidefinite, it can be shown that the function $\phi(\lambda)$ is convex on I and thus a safeguarded version of Newton's method is a reasonable choice for the solution of this equation. This is the approach used by Moré and Sorenson [15] for solving the TRS which at each iteration makes use of the Cholesky decomposition and hence is not proper for large-scale problems. If B is indefinite, then $\phi(\lambda)$ may not be convex or concave and hence there is no guarantee that Newton's method will be convergent [16]. Here, we propose an algorithm for the solution of $\phi(\lambda) = 0$ which is indeed the bisection method occupied with two techniques to accelerate its convergence [17, 21].

Algorithm for solving equation $\phi(\lambda) = 0$

Iterate until a termination criterion is met:

1. Set λ_{new} to the midpoint of the interval containing λ^* .
2. If the points at which $\phi(\lambda)$ has positive and negative values are available, do inverse linear interpolation, update λ_{new} if inverse linear interpolation is successful.
3. At λ_{new} , take a step to the boundary if points at which $\phi(\lambda)$ has positive and negative values are known.

End loop.

In what follows, we explain two techniques used in the algorithm.

Inverse Interpolation

Let $[\lambda_b, \lambda_g]$ be the current interval containing λ^* . Moreover, suppose the relation (5) does not hold. Then, by Lemma 2, $\phi(\lambda)$ is strictly decreasing and hence, we can consider its inverse function. We approximate the inverse function $\lambda(\phi)$ by a linear function. Then we set $\lambda_{new} = \lambda(0)$ if $\lambda(0) \in [\lambda_b, \lambda_g]$.

Primal step to the boundary

Let x^* denote the optimal solution of QCQP. It can be shown that as the algorithm proceeds, λ_{new} converges to the λ^* , the optimal Lagrange multiplier and hence, the sequence $x(\lambda)$ also will be convergent to x^* . Now, suppose that there exist values λ_b and λ_g with $\phi(\lambda_b) > 0$ and $\phi(\lambda_g) < 0$. Then, we can take an inexpensive primal step to the point $\alpha x(\lambda_b) + (1 - \alpha)x(\lambda_g)$ on the boundary by choosing a suitable step length α . This likely improves the objective value. We note that the resulting sequence is also convergent to x^* .

Computing $\phi(\lambda)$

At each iteration of the algorithm, $\phi(\lambda)$ is computed by applying the conjugate gradient algorithm to the positive definite system of linear equations

$$(A + \lambda B)x(\lambda) = -(a + \lambda b). \quad (12)$$

The conjugate-gradient method is one of the most widely used iterative methods for solving symmetric positive-definite linear equations. In hard case 1 when λ^* is near to $\bar{\lambda}$ or $\underline{\lambda}$, system (12) may become ill-conditioned. In the following two theorems (Theorems 2 and 3), we show that, to overcome near singularity, one can solve an alternative well-conditioned positive definite system that has the same solution as (12). Before stating that, we need the following proposition and lemma.

Proposition 3 *Suppose that Assumption 2 holds. Then (λ, v) is an eigenpair of the pencil $(A, -B)$ if and only if $(-\frac{1}{\lambda - \bar{\lambda}}, (A + \hat{\lambda}B)^{\frac{1}{2}}v)$ is an eigenpair of matrix $(A + \hat{\lambda}B)^{-\frac{1}{2}}B(A + \hat{\lambda}B)^{-\frac{1}{2}}$.*

Proof (λ, v) is an eigenpair of pencil $(A, -B)$ if and only if $(A + \lambda B)v = 0$, implying that $(A + \hat{\lambda}B + (\lambda - \hat{\lambda})B)v = 0$. Since $(A + \hat{\lambda}B) \succ 0$, it follows that $(I + (\lambda - \hat{\lambda})(A + \hat{\lambda}B)^{-\frac{1}{2}}B(A + \hat{\lambda}B)^{-\frac{1}{2}})(A + \hat{\lambda}B)^{\frac{1}{2}}v = 0$. Note that $\lambda \neq \hat{\lambda}$ because $\det(A + \hat{\lambda}B) \neq 0$. This implies that $((A + \hat{\lambda}B)^{-\frac{1}{2}}B(A + \hat{\lambda}B)^{-\frac{1}{2}} + \frac{1}{\lambda - \hat{\lambda}}I)(A + \hat{\lambda}B)^{\frac{1}{2}}v = 0$ which completes the proof. \square

Lemma 3 *Suppose that $\lambda \neq \hat{\lambda}$. Then $(a + \lambda b) \in \text{Range}(A + \lambda B)$ if and only if $(-b + B(A + \hat{\lambda}B)^{-1}(a + \hat{\lambda}b)) \in \text{Range}(A + \lambda B)$.*

Proof $(a + \lambda b) \in \text{Range}(A + \lambda B)$ if and only if there exists \bar{x} such that $(A + \lambda B)\bar{x} = -(a + \lambda b)$. This implies that

$$[(A + \hat{\lambda}B) + (\lambda - \hat{\lambda})B]\bar{x} = -[(a + \hat{\lambda}b) + (\lambda - \hat{\lambda})b].$$

Next, the change of variable $\bar{x} = \bar{y} - (A + \hat{\lambda}B)^{-1}(a + \hat{\lambda}b)$ gives

$$(A + \lambda B)\bar{y} = (\lambda - \hat{\lambda})(-b + B(A + \hat{\lambda}B)^{-1}(a + \hat{\lambda}b)), \quad (13)$$

implying that $(-b + B(A + \hat{\lambda}B)^{-1}(a + \hat{\lambda}b)) \in \text{Range}(A + \lambda B)$. \square

Theorem 2 *Suppose that $(a + \lambda b) \in \text{Range}(A + \lambda B)$. Moreover, assume that the set $\{v_1, \dots, v_r\}$ is a basis of $\text{Null}(A + \lambda B)$ that is $(A + \hat{\lambda}B)$ -orthogonal, i.e., $v_i^T(A + \hat{\lambda}B)v_i = 1$ and $v_i^T(A + \hat{\lambda}B)v_j = 0$ for all $i \neq j$. Let $\hat{\lambda} \neq \lambda \in (\underline{\lambda}, \bar{\lambda})$, then x^* is the solution of system*

$$(A + \lambda B)x = -(a + \lambda b), \quad (14)$$

if and only if $y^* = x^* + z$ is the solution of

$$[A + \lambda B + \alpha \sum_{i=1}^r (A + \hat{\lambda}B)v_i v_i^T (A + \hat{\lambda}B)]y = (\lambda - \hat{\lambda})(Bz - b) \quad (15)$$

where $z = (A + \hat{\lambda}B)^{-1}(a + \hat{\lambda}b)$ and α is an arbitrary positive constant. The same assertion holds when $\underline{\lambda}$ is replaced by $\bar{\lambda}$.

Proof It is easy to see that x^* is the unique solution of system (14) if and only if $y^* = x^* + z$ is the solution of

$$(A + \lambda B)y = (\lambda - \hat{\lambda})(Bz - b). \quad (16)$$

To prove the theorem, it is sufficient to show that systems (16) and (15) are equivalent. System (15) can be rewritten as follows:

$$[(A + \hat{\lambda}B) + (\lambda - \hat{\lambda})B + \alpha \sum_{i=1}^r (A + \hat{\lambda}B)v_i v_i^T (A + \hat{\lambda}B)]y = (\lambda - \hat{\lambda})(Bz - b).$$

Since $(A + \hat{\lambda}B) \succ 0$, we have

$$\begin{aligned} [I + (\lambda - \hat{\lambda})(A + \hat{\lambda}B)^{-\frac{1}{2}}B(A + \hat{\lambda}B)^{-\frac{1}{2}} + \alpha \sum_{i=1}^r (A + \hat{\lambda}B)^{\frac{1}{2}}v_i v_i^T (A + \hat{\lambda}B)^{\frac{1}{2}}](A + \hat{\lambda}B)^{\frac{1}{2}}y \\ = (\lambda - \hat{\lambda})(A + \hat{\lambda}B)^{-\frac{1}{2}}(Bz - b). \end{aligned} \quad (17)$$

Set $M = (A + \hat{\lambda}B)^{-\frac{1}{2}}B(A + \hat{\lambda}B)^{-\frac{1}{2}}$, then by Proposition 3, $q_i = (A + \hat{\lambda}B)^{\frac{1}{2}}v_i, i = 1, \dots, r$, are the eigenvectors of M corresponding to the eigenvalue $-\frac{1}{\hat{\lambda}-\lambda}$. Note that $q_i^T q_i = 1$ for $i = 1, \dots, r$ and $q_i^T q_j = 0$ for all $i \neq j \in \{1, \dots, r\}$. Without loss of generality, let $M = QDQ^T$ be the eigenvalue decomposition of M in which Q contains $q_i = 1, \dots, r$ as its r first columns. From (17) we get

$$[I + (\lambda - \hat{\lambda})D + \alpha \sum_{i=1}^r Q^T (A + \hat{\lambda}B)^{\frac{1}{2}} v_i v_i^T (A + \hat{\lambda}B)^{\frac{1}{2}} Q] Q^T (A + \hat{\lambda}B)^{\frac{1}{2}} y = (\lambda - \hat{\lambda}) Q^T (A + \hat{\lambda}B)^{-\frac{1}{2}} (Bz - b). \quad (18)$$

Furthermore, we have

$$Q^T (A + \hat{\lambda}B)^{\frac{1}{2}} v_i v_i^T (A + \hat{\lambda}B)^{\frac{1}{2}} Q = e_i e_i^T, \quad i = 1, \dots, r, \quad (19)$$

due to the fact that

$$q_k^T (A + \hat{\lambda}B)^{\frac{1}{2}} v_i v_i^T (A + \hat{\lambda}B)^{\frac{1}{2}} q_j = \begin{cases} 1 & \text{if } k = j = i \in \{1, \dots, r\}, \\ 0 & \text{otherwise,} \end{cases}$$

where e_i is the unit vector and $q_i, i = 1, \dots, n$, denote i 'th column of Q . Therefore, it follows from (18) and (19) that

$$(I + (\lambda - \hat{\lambda})D + \alpha \sum_{i=1}^r e_i e_i^T) Q^T (A + \hat{\lambda}B)^{\frac{1}{2}} y = (\lambda - \hat{\lambda}) Q^T (A + \hat{\lambda}B)^{-\frac{1}{2}} (Bz - b). \quad (20)$$

Now since $(a + \underline{\lambda}b) \in \text{Range}(A + \underline{\lambda}B)$, by Lemma 3, $(Bz - b) \in \text{Range}(A + \underline{\lambda}B)$ and consequently $v_i^T (Bz - b) = 0$ for $i = 1, \dots, r$. This implies that

$$q_i^T (A + \hat{\lambda}B)^{-\frac{1}{2}} (Bz - b) = 0, \quad i = 1, \dots, r.$$

Therefore, the r first components of the right hand side vector in system (20) are zero. Further let $c_i, i = 1, \dots, r$, denote the r first diagonal elements of matrix $(I + (\lambda - \hat{\lambda})D)$. By Proposition 3, it is easy to see that $c_i = \frac{\lambda - \hat{\lambda}}{\hat{\lambda} - \lambda} > 0, i = 1, \dots, r$. Since $\alpha > 0$, the above discussion proves that system (20) is equivalent to the following system:

$$(I + (\lambda - \hat{\lambda})D) Q^T (A + \hat{\lambda}B)^{\frac{1}{2}} y = (\lambda - \hat{\lambda}) Q^T (A + \hat{\lambda}B)^{-\frac{1}{2}} (Bz - b).$$

This is also equivalent to

$$(A + \lambda B)y = (\lambda - \hat{\lambda})(Bz - b),$$

which completes the proof. When $\underline{\lambda}$ is replaced by $\bar{\lambda}$, the assertion can be proved in a similar manner. \square

Theorem 3 Suppose that $(a + \underline{\lambda}b) \in \text{Range}(A + \underline{\lambda}B)$. Moreover, assume that the set $\{v_1, \dots, v_r\}$ is a basis of $\text{Null}(A + \underline{\lambda}B)$ that is $(A + \hat{\lambda}B)$ -orthogonal, i.e., $v_i^T (A + \hat{\lambda}B)v_i = 1$ and $v_i^T (A + \hat{\lambda}B)v_j = 0$ for all $i \neq j$. Then matrix $\tilde{A} = A + \underline{\lambda}B + \alpha \sum_{i=1}^r (A + \hat{\lambda}B)v_i v_i^T (A + \hat{\lambda}B)$ is positive definite. The same assertion holds when $\underline{\lambda}$ is replaced by $\bar{\lambda}$.

Proof Since $A + \underline{\lambda}B \succeq 0$ and $\sum_{i=1}^r (A + \hat{\lambda}B)v_i v_i^T (A + \hat{\lambda}B) \succeq 0$, then $\tilde{A} \succeq 0$. To show that $\tilde{A} \succ 0$ it is sufficient to prove that if $x^T \tilde{A} x = 0$ for $x \in \mathbb{R}^n$, then $x = 0$. For any $x \in \mathbb{R}^n$, there exist unique $x_1 \in \text{Null}(A + \underline{\lambda}B)$ and $x_2 \in \text{Range}(A + \underline{\lambda}B)$ such that $x = x_1 + x_2$. We have

$$x^T(\tilde{A})x = x_2^T(A + \underline{\lambda}B)x_2 + \alpha \sum_{i=1}^r (v_i^T(A + \hat{\lambda}B)x)^2 = 0.$$

This implies that

$$x_2^T(A + \underline{\lambda}B)x_2 = 0, \quad v_i^T(A + \hat{\lambda}B)x = 0, \quad i = 1, \dots, r. \quad (21)$$

Since $(A + \underline{\lambda}B) \succeq 0$, we obtain $(A + \underline{\lambda}B)x_2 = 0$, and hence $x_2 \in \text{Null}(A + \underline{\lambda}B)$. Together with the assumption that $x_2 \in \text{Range}(A + \underline{\lambda}B)$ we obtain $x_2 = 0$. Thus $x = x_1$. On the other hand x_1 can be written as $x_1 = \sum_{j=1}^r c_j v_j$ where $c_j \in \mathbb{R}$ for $j = 1, \dots, r$. So it follows from (21) that $\sum_{j=1}^r c_j v_j^T (A + \hat{\lambda}B)v_j = 0$ for $i = 1, \dots, r$, resulting in $c_j = 0$ for $j = 1, \dots, r$. Therefore $x_1 = 0$ and consequently $x = 0$, which completes the proof. When $\underline{\lambda}$ is replaced by $\bar{\lambda}$, the assertion can be proved in a similar manner. \square

4 Numerical Experiments

In this section, on several randomly generated problems of various dimensions, we compare the proposed conjugate gradient-based algorithm (CGB) with Algorithms 1 and 2 from [12] and Algorithm 3.2 from [2]. The comparison with Algorithm 3.2 of [2] is done for dimension up to 5000 as it needs longer time to solve larger dimensions. All computations are performed in MATLAB 8.5.0.197613 on a 1.70 GHz laptop with 4 GB of RAM. Throughout the paper, we have assumed that there exists $\hat{\lambda}$ such that $A + \hat{\lambda}B \succ 0$. In practice $\hat{\lambda}$ is usually unknown in advance, but since all four algorithms require it for initialization, we assume that $\hat{\lambda}$ is known and skip its computation. However, the algorithms in [4, 10, 16] can be used to find $\hat{\lambda}$. We use the stopping criterion

$$\max \{|\phi(\lambda)|, \|(A + \lambda B)x + (a + \lambda b)\|\} < 10^{-8},$$

or

$$\frac{|\text{high} - \text{low}|}{|\text{high}| + |\text{low}|} < 10^{-11}$$

for solving the equation $\phi(\lambda) = 0$ where x is the best feasible solution of QCQP obtained up to the current iteration and $[\text{low}, \text{high}]$ is the interval containing λ^* at the current iteration. We set $\epsilon_1 = 10^{-10}$, $\epsilon_2 = 10^{-13}$ and $\epsilon_3 = 10^{-10}$ in Algorithms 1 and 2 from [12]. As in [12], to compute $\underline{\lambda}$ and $\bar{\lambda}$, the generalized eigenvalue problem is solved by `eigifp`¹. To verify hard case 2, as described in Section 3.1, we need to compute an orthonormal basis of $\text{Null}(A + \underline{\lambda}B)$ or $\text{Null}(A + \bar{\lambda}B)$. Recall that $A + \underline{\lambda}B$ and $A + \bar{\lambda}B$ are singular and positive semidefinite. Thus, a nullspace vector

¹ `eigifp` is a MATLAB program for computing a few algebraically smallest or largest eigenvalues and their corresponding eigenvectors of the generalized eigenvalue problem, available from <http://www.ms.uky.edu/~qye/software.html>.

of $A + \underline{\lambda}B$ and $A + \bar{\lambda}B$ can be found by finding an eigenvector corresponding to the smallest eigenvalue, i.e., 0, which in our numerical tests, is done by `eigifp`. We apply the Newton refinement process in Section 4.1.2 of [2] to all four algorithms to improve the accuracy of the solution. For simplicity, we consider QCQP with nonsingular B including positive definite and indefinite B . Hence, we can assume without loss of generality that $b = 0$. Our test problems include both easy and hard case (case 1 and case 2) instances.

4.1 First class of test problems

In this class of test problems, we consider QCQP with positive definite A and indefinite B . Thus, we set $\hat{\lambda} = 0$. We follow Procedure 1, Procedure 2 and Procedure 3 to generate an easy case, hard case 1 and hard case 2 instance, respectively

Procedure 1. (Generating an easy case instance)

We first generate randomly a sparse positive definite matrix A and a sparse indefinite matrix B via `A=sprandsym(n,density,1/cond,2)` and `B = sprandsym(n,density)` where `cond` refers to condition number. After computing $\bar{\lambda}$, we set $a = -(A + \bar{\lambda}B)x_0$, where x_0 is computed via `x0=randn(n,1)/10` and λ is chosen uniformly from $(0, \bar{\lambda})$. Next, to avoid generating a QCQP having an interior solution, we chose β randomly from $(-s, -\ell)$ where $s = x_c^T B x_c$, $\ell = x_0^T B x_0$ and x_c is the solution of linear system $Ax = -a$. From the optimality conditions we see that the above construction likely gives an easy case instance.

Procedure 2. (Generating a hard case 1 instance)

We generate A , B , x_0 and β as the above procedure but we set $a = -(A + \bar{\lambda}B)x_0$. From the optimality conditions we see that this construction gives a hard case 1 instance.

Procedure 3. (Generating a hard case 2 instance)

We generate A , B and a as Procedure 2 but we set $\beta = -\ell$.

We set `cond` = 10, 100, 1000 and for each dimension and each condition number, we generated 10 instances, and the corresponding numerical results are adjusted in Tables 1 and 2, where we report the average runtime in second (Time) and accuracy (Accuracy). To measure the accuracy, we have computed the relative objective function difference as follows:

$$\frac{q(x^*) - q(x_{best})}{|q(x_{best})|},$$

where x^* is the computed solution by each method and x_{best} is the solution with the smallest objective value among the four algorithms. We use "Alg1" and "Alg2" to denote Algorithms 1 and 2 in [12], respectively, and "Alg3" to denote Algorithm 3.2 in [2].

4.2 Second class of test problems

We first generate randomly a sparse positive definite matrix C and a sparse indefinite matrix B via `C=sprandsym(n,density,1/cond,2)` and `B = sprandsym(n,density)`.

Table 1: Computational results of the first class of test problems with density=1e-2

	n	Time(s)				Accuracy			
		CGB	Alg1	Alg2	Alg3	CGB	Alg1	Alg2	Alg3
cond=10									
Easy Case	1000	0.24	0.32	0.27	0.60	0.0000e+00	1.3534e-14	2.9908e-14	2.703592e-16
	2000	0.36	0.43	0.36	3.85	9.5123e-17	2.1722e-15	2.7597e-15	4.640596e-17
	3000	0.50	0.79	0.52	11.56	4.4606e-17	5.4207e-16	3.9725e-16	7.106022e-17
	4000	0.92	1.40	1.24	30.17	2.4456e-16	1.7972e-15	2.2517e-15	1.711915e-16
	5000	1.14	1.66	1.25	417.53	4.0827e-16	4.2164e-16	4.5748e-16	2.455677e-16
cond=100									
Easy Case	1000	0.56	0.74	0.58	0.54	2.2119e-16	7.7736e-13	1.3902e-11	2.089449e-16
	2000	0.87	1.16	0.92	3.61	6.9482e-17	1.2703e-13	5.0994e-13	1.123734e-16
	3000	1.98	2.84	2.32	12.70	1.2295e-16	6.3770e-14	2.6147e-12	4.2882e-17
	4000	1.98	2.84	2.32	50.70	1.6666e-16	4.2965e-14	4.6357e-13	5.4903e-17
	5000	4.18	6.97	5.16	673.36	2.5057e-16	1.8041e-14	5.3498e-14	1.4510e-17
cond=1000									
Easy Case	1000	3.75	5.33	4.13	0.56	1.3319e-16	1.2508e-11	1.5758e-09	3.415593e-16
	2000	4.29	6.47	4.45	3.84	1.5526e-16	3.3995e-12	2.8861e-10	1.421543e-16
	3000	8.59	17.89	9.56	12.17	4.3130e-15	1.2760e-12	8.4678e-11	2.068219e-16
	4000	10.56	18.10	13.71	41.88	1.2220e-15	5.5054e-13	1.1153e-11	6.020699e-17
	5000	16.36	30.95	21.69	371.55	1.7654e-16	4.5521e-13	3.9881e-11	1.804393e-16
cond=10									
Hard Case 1	1000	0.29	0.30	0.23	0.68	2.5820e-16	4.6885e-14	4.7315e-13	2.141403e-16
	2000	0.49	1.53	0.72	5.33	8.9252e-17	2.9432e-13	3.1029e-11	9.468005e-17
	3000	1.60	1.87	1.56	18.63	8.8924e-17	1.0251e-14	8.0005e-14	8.529213e-17
	4000	1.34	1.63	1.50	48.54	7.6730e-17	4.5916e-15	5.3948e-15	1.863880e-16
	5000	6.09	9.09	6.59	307.54	1.7215e-16	4.9540e-15	2.8191e-15	4.814561e-16
cond=100									
Hard Case 1	1000	0.37	0.72	0.33	0.61	3.4527e-16	2.1326e-12	1.1098e-10	1.517419e-16
	2000	0.70	2.26	1.07	4.40	1.4639e-16	1.8446e-12	2.0338e-11	1.263138e-16
	3000	3.46	4.41	3.29	12.75	4.1817e-16	1.5004e-13	1.8512e-12	5.416258e-17
	4000	5.36	8.24	6.14	43.24	2.8051e-16	2.1693e-13	6.9215e-12	1.061026e-16
	5000	9.04	13.48	10.05	310.26	8.2448e-17	6.1508e-14	1.5047e-13	4.103097e-17
cond=1000									
Hard Case 1	1000	1.41	6.77	1.38	0.70	1.7472e-16	1.0359e-10	6.6120e-09	1.024406e-16
	2000	4.52	7.23	4.77	4.04	3.6154e-16	3.4160e-12	2.2689e-10	1.746964e-16
	3000	11.11	29.03	13.83	20.93	1.5364e-16	9.3206e-11	2.6199e-09	1.716415e-16
	4000	23.37	47.93	27.75	52.19	1.3664e-16	1.7287e-12	1.0004e-10	1.511822e-16
	5000	21.09	46.43	28.84	402.58	6.0663e-16	1.5179e-12	2.0300e-10	2.686279e-16
cond=10									
Hard Case 2	1000	0.26	0.88	0.36	3.00	7.4723e-17	4.9359e-13	4.8652e-11	5.471231e-16
	2000	0.36	1.58	0.73	16.70	0.0000e+00	1.6001e-13	3.8674e-13	3.896115e-16
	3000	0.77	7.40	2.45	173.19	3.4482e-16	2.4531e-13	7.8146e-11	3.030414e-16
	4000	1.44	12.18	3.98	852.45	4.5639e-17	8.9613e-14	1.3460e-12	2.422850e-16
	5000	2.03	30.51	5.31	1463.27	3.0985e-16	2.0535e-13	3.5345e-12	1.831296e-16
cond=100									
Hard Case 2	1000	0.62	7.21	2.12	4.23	2.1081e-16	2.7349e-11	4.0860e-09	6.574916e-16
	2000	1.01	7.94	3.01	15.10	1.3175e-16	3.5787e-12	5.1980e-10	8.660221e-17
	3000	2.71	46.79	9.41	236.70	1.0358e-16	1.3325e-11	2.5842e-09	9.794199e-17
	4000	4.29	118.69	20.47	495.63	6.4502e-17	7.7936e-12	3.0469e-09	6.557389e-17
	5000	8.22	209.70	52.54	697.56	1.2621e-16	6.3835e-12	7.1765e-10	6.557389e-17
cond=1000									
Hard Case 2	1000	2.16	14.14	4.75	3.24	3.6635e-16	3.9804e-09	5.2611e-08	1.920469e-16
	2000	3.49	31.50	7.13	29.45	4.3374e-17	6.5600e-09	1.9302e-08	1.173405e-16
	3000	9.67	122.63	27.69	79.25	4.2925e-17	3.2570e-09	3.9270e-08	2.720614e-16
	4000	12.81	167.30	43.43	599.55	1.2716e-16	1.9239e-08	1.0997e-08	1.315645e-16
	5000	17.62	245.88	83.07	1151.76	2.1056e-16	2.6294e-08	3.0084e-08	1.324996e-16

Table 2: Computational results of the first class of test problems with density=1e-4

	n	Time(s)			Accuracy		
		CGB	Alg1	Alg2	CGB	Alg1	Alg2
cond=10							
Easy Case	10000	0.47	0.62	0.43	1.1725e-15	2.9305e-15	1.9469e-15
	20000	1.10	1.65	1.10	1.6881e-15	7.8945e-16	6.9847e-16
	30000	1.43	2.29	1.34	8.5874e-16	5.0097e-16	4.8177e-16
	40000	2.78	4.07	2.82	3.9322e-16	8.6336e-16	6.7728e-16
	50000	3.53	5.74	3.82	2.1866e-16	1.5472e-15	1.6432e-14
cond=100							
Easy Case	10000	2.79	3.69	2.84	0.0000e+00	5.1216e-13	9.4987e-12
	20000	4.23	6.40	4.73	0.0000e+00	5.3774e-14	1.7939e-13
	30000	4.43	6.05	4.52	0.0000e+00	2.2114e-14	7.4127e-14
	40000	8.26	12.96	8.76	1.6904e-16	2.7534e-14	9.8461e-14
	50000	8.70	11.88	9.25	2.9568e-16	9.3602e-15	2.6464e-15
cond=1000							
Easy Case	10000	8.48	13.33	9.09	0.0000e+00	6.7834e-12	7.8038e-10
	20000	14.55	23.77	16.44	0.0000e+00	7.7513e-13	2.9847e-11
	30000	23.90	40.75	27.00	0.0000e+00	4.3943e-13	1.2151e-11
	40000	44.37	71.48	50.39	0.0000e+00	3.7856e-13	5.2588e-12
	50000	54.38	84.49	63.40	0.0000e+00	2.6751e-13	4.2168e-12
cond=10							
Hard Case 1	10000	0.88	0.96	0.64	5.5224e-17	2.2499e-14	2.7961e-13
	20000	1.60	1.58	1.08	3.6226e-16	5.7196e-15	1.0666e-14
	30000	3.61	3.90	2.88	4.2608e-16	1.6371e-14	2.1939e-14
	40000	4.34	3.87	2.40	1.7872e-15	2.1961e-15	2.1956e-16
	50000	6.73	6.72	5.20	1.1921e-15	1.6576e-14	6.3980e-15
cond=100							
Hard Case 1	10000	2.91	4.10	2.65	0.0000e+00	1.0370e-12	3.1089e-11
	20000	4.40	5.36	3.30	0.0000e+00	1.0955e-13	1.4446e-11
	30000	12.51	14.60	7.99	0.0000e+00	2.4296e-13	8.2524e-13
	40000	10.66	10.68	7.37	3.2416e-15	1.7511e-14	1.8957e-14
	50000	19.62	16.69	11.66	5.8187e-15	9.0692e-15	3.5658e-15
cond=1000							
Hard Case 1	10000	19.04	20.76	14.89	0.0000e+00	7.8027e-12	1.6214e-09
	20000	28.85	45.77	27.56	0.0000e+00	1.5992e-12	1.1197e-10
	30000	41.50	64.18	42.81	0.0000e+00	9.0035e-13	2.7761e-11
	40000	60.11	106.70	61.81	0.0000e+00	9.8912e-13	2.2214e-11
	50000	58.34	93.55	58.01	0.0000e+00	4.6131e-13	4.4259e-12
cond=10							
Hard Case 2	10000	0.41	4.25	1.22	0.0000e+00	2.3268e-13	5.8761e-11
	20000	0.76	3.50	1.04	0.0000e+00	5.8964e-14	7.2553e-14
	30000	1.74	25.12	9.12	0.0000e+00	6.8237e-13	5.6535e-12
	40000	2.06	14.36	6.11	0.0000e+00	1.3294e-13	3.8901e-13
	50000	2.78	14.73	5.20	0.0000e+00	1.0006e-13	7.4351e-14
cond=100							
Hard Case 2	10000	1.78	15.16	3.42	0.0000e+00	5.5265e-10	5.1118e-09
	20000	1.84	25.53	5.79	0.0000e+00	6.0442e-12	9.0442e-10
	30000	2.61	30.48	7.78	0.0000e+00	8.1750e-13	1.6605e-11
	40000	4.39	91.63	16.24	0.0000e+00	4.7839e-12	1.4334e-10
	50000	7.59	136.59	27.00	0.0000e+00	4.5553e-11	1.3001e-10
cond=1000							
Hard Case 2	10000	4.70	38.58	9.19	0.0000e+00	1.5298e-08	1.2372e-07
	20000	7.41	92.02	20.77	0.0000e+00	6.0570e-09	2.0386e-08
	30000	34.75	293.60	79.92	0.0000e+00	9.4080e-10	9.4997e-10
	40000	57.08	344.94	70.91	0.0000e+00	1.5930e-10	3.6650e-09
	50000	53.14	631.03	138.77	0.0000e+00	1.0949e-10	6.6408e-10

Next, we set $A = C - B$. In this case, obviously, we can set $\hat{\lambda} = 1$. We follow Procedure 1 to generate an easy case instance but we choose λ uniformly from $(\underline{\lambda}, \bar{\lambda})$ and if $s > \ell$, we choose β randomly from $(-s, -\ell)$ else we choose β from $(-\ell, -s)$ where $s = x_c^T B x_c$ and s is the solution of linear system $Cx = -a$. Procedure 2 and 3 are followed to generate hard case (case 1 and 2) instances. The numerical results are adjusted in Tables 3 and 4.

As we see in Tables 1 and 3, for 90% of the generated instances, CGB algorithm is faster than Algorithm 3.2 from [2] while having comparable accuracy. The time difference become significant when we increase the dimension, since Algorithm 3.2 requires computing an extremal eigenpair of an $(2n + 1) \times (2n + 1)$ generalized eigenvalue problem which is time-consuming when the involved matrices are not highly sparse.

From Tables 1, 2, 3 and 4, we observe that CGB algorithm computes more accurate solutions than Algorithms 1 and 2. Moreover, except for one dimension, it is always faster than Algorithm 1 and when we increase the dimension, the time difference become significant. For easy case problems, CGB Algorithm is faster than Algorithm 2 for about 77% of cases, specifically, CGB Algorithm is more efficient than Algorithm 2 when condition number is large. In hard Case 2, CGB Algorithm is much more efficient than Algorithms 1 and 2 because it first checks for hard case 2, if it is the case, the optimal solution of QCQP is computed via solving a positive definite system of linear equations. In hard case 1, CGB algorithm is slower than Algorithm 2 for about 60 % of the cases but still faster than Algorithm 1 because of the extra time it take for verifying hard case 2.

5 Conclusions

In this paper, we have considered the problem of minimizing a general quadratic function subject to one general quadratic constraint. A conjugate gradient-based algorithm is introduced to solve the problem which is based on solving a sequence of positive definite system of linear equations by conjugate gradient method. Our computational experiments on several randomly generated test problems show that the proposed method is efficient for large sparse instances since the most expensive operations at each iteration is several matrix vector products, that are cheap when the matrix is sparse.

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Table 3: Computational results of the second class of test problems with density=1e-2

	n	Time(s)				Accuracy			
		CGB	Alg1	Alg2	Alg3	CGB	Alg1	Alg2	Alg3
cond=10									
Easy Case	1000	0.19	0.25	0.22	0.61	1.8361e-16	2.3145e-14	1.4939e-13	1.806630e-16
	2000	0.35	0.48	0.40	4.04	1.1614e-16	1.0821e-14	2.3359e-14	1.129161e-16
	3000	0.60	0.75	1.06	12.71	1.6823e-16	1.8640e-15	2.6605e-15	7.371001e-17
	4000	1.02	1.39	1.75	28.59	7.3294e-17	1.4715e-15	3.4793e-13	1.517022e-16
	5000	3.02	3.77	2.34	325.90	6.2226e-16	2.7151e-16	4.2262e-16	6.980376e-17
cond=100									
Easy Case	1000	0.48	1.02	0.71	0.62	5.2875e-16	2.6805e-12	4.0940e-11	1.715593e-15
	2000	0.91	1.51	1.10	3.78	3.0586e-16	2.2825e-13	1.5995e-12	0
	3000	1.92	2.55	2.00	13.62	2.3203e-15	2.7241e-13	1.1253e-12	1.952349e-16
	4000	2.87	4.06	3.20	36.20	1.0388e-15	2.5531e-13	1.2496e-12	6.361166e-16
	5000	4.14	5.14	4.32	234.46	1.1003e-15	1.0004e-13	3.9197e-13	1.497476e-16
cond=1000									
Easy Case	1000	1.85	3.25	2.02	0.55	2.3202e-16	6.2333e-11	1.3809e-04	3.307807e-16
	2000	5.42	8.53	6.08	4.80	5.8536e-17	2.1502e-12	2.3546e-10	3.576414e-16
	3000	12.98	19.32	13.94	14.35	8.4864e-17	1.3869e-12	4.7013e-11	1.324596e-16
	4000	10.09	22.45	11.43	38.59	1.4693e-16	7.1405e-13	8.7914e-11	4.308794e-17
	5000	19.00	30.42	22.90	385.47	1.0816e-16	3.9543e-13	6.7996e-12	1.596002e-16
cond=10									
Hard Case 1	1000	0.44	0.47	0.34	0.80	7.6776e-17	3.4128e-14	1.3917e-13	2.167390e-16
	2000	0.65	0.88	0.60	5.25	3.2993e-17	7.8537e-14	3.1866e-12	1.040181e-16
	3000	1.42	1.45	1.13	15.14	9.2671e-17	1.2647e-14	2.0693e-09	6.589870e-17
	4000	1.70	1.22	1.02	35.27	7.2135e-17	1.7775e-15	2.4309e-15	8.207300e-17
	5000	6.44	6.86	4.31	401.36	2.2950e-16	1.5855e-14	2.0637e-13	2.502850e-17
cond=100									
Hard Case 1	1000	0.75	0.99	0.65	0.57	1.2815e-16	1.3903e-12	1.3202e-10	4.722266e-17
	2000	1.33	1.95	1.16	4.42	5.7397e-17	5.4877e-13	1.6352e-11	1.161957e-16
	3000	4.05	3.24	2.72	13.22	7.5077e-17	1.1536e-13	2.6095e-12	2.778583e-17
	4000	5.65	11.97	5.54	40.99	9.2310e-17	7.0747e-13	5.3772e-11	4.250603e-17
	5000	11.21	10.75	7.45	332.81	2.0919e-16	3.5848e-14	6.5684e-13	2.048992e-17
cond=1000									
Hard Case 1	1000	2.34	4.41	1.99	0.78	4.8791e-17	1.0518e-11	1.6066e-06	1.053864e-16
	2000	4.40	10.19	4.57	4.36	1.1762e-16	4.4629e-12	4.1546e-10	4.459648e-17
	3000	15.41	28.43	12.78	14.62	1.1966e-13	3.0246e-12	2.3939e-10	8.079233e-17
	4000	13.81	33.07	12.23	27.22	7.3406e-15	2.0796e-12	7.9221e-10	4.955689e-17
	5000	34.44	151.09	45.20	263.30	3.1287e-15	1.2173e-09	1.4141e-08	4.955689e-17
cond=10									
Hard Case 2	1000	0.33	0.86	0.36	3.24	0.0000e+00	3.8490e-13	1.8209e-12	6.857462e-16
	2000	0.99	8.64	2.41	85.23	0.0000e+00	6.4555e-13	1.8722e-11	3.651448e-16
	3000	1.10	4.00	1.83	65.52	0.0000e+00	7.5183e-14	3.9460e-13	6.287905e-17
	4000	1.88	16.77	3.24	487.32	3.4636e-16	1.3285e-13	4.2813e-12	0.0000e+00
	5000	2.45	20.90	6.64	909.38	5.4219e-16	6.9743e-13	3.0042e-11	0.0000e+00
cond=100									
Hard Case 2	1000	0.53	2.39	1.05	1.32	2.6963e-16	4.9522e-12	2.9811e-10	4.770832e-16
	2000	1.00	9.40	2.90	28.23	4.0417e-16	6.6325e-12	5.2118e-10	1.133704e-16
	3000	2.87	58.94	9.74	107.78	2.9495e-16	5.7992e-12	9.2886e-10	0.0000e+00
	4000	4.92	31.57	8.35	147.59	2.9235e-16	1.0990e-12	1.7460e-10	0.0000e+00
	5000	7.96	160.04	48.60	1308.83	0.0000e+00	2.9739e-12	4.4620e-10	2.581425e-16
cond=1000									
Hard Case 2	1000	2.68	14.00	6.01	4.06	2.9054e-16	8.7283e-08	1.5660e-07	0
	2000	5.68	31.84	12.25	18.86	2.5527e-16	1.2073e-08	8.0504e-08	6.035149e-17
	3000	12.38	94.31	29.17	53.89	2.2569e-16	5.4429e-09	1.0046e-07	1.214486e-16
	4000	10.80	152.22	29.82	174.29	6.0252e-17	5.2876e-09	2.9837e-08	5.656610e-17
	5000	48.30	276.64	70.15	449.92	2.0865e-16	1.8989e-08	3.4265e-08	2.959448e-16

Table 4: Computational results of the second class of test problems with density=1e-4

	n	Time(s)			Accuracy		
		CGB	Alg1	Alg2	CGB	Alg1	Alg2
cond=10							
Easy Case	10000	0.71	0.84	0.71	2.9910e-17	2.5167e-15	6.1729e-15
	20000	0.90	1.47	0.87	2.9690e-16	1.0642e-15	2.6536e-15
	30000	1.83	2.72	2.27	3.6312e-16	1.5595e-15	2.8782e-15
	40000	2.96	4.45	3.10	3.0619e-16	1.0188e-15	6.8731e-16
	50000	5.74	8.34	6.34	3.5265e-16	9.1985e-16	1.9643e-15
cond=100							
Easy Case	10000	1.66	2.16	1.62	0.0000e+00	5.1889e-13	4.9398e-12
	20000	2.99	5.67	3.15	0.0000e+00	2.0833e-13	7.7965e-12
	30000	9.62	13.68	9.71	0.0000e+00	4.1471e-14	2.4518e-13
	40000	12.88	17.67	13.24	0.0000e+00	3.4451e-14	6.7671e-13
	50000	13.67	20.62	13.65	1.6836e-16	1.2681e-14	1.3899e-14
cond=1000							
Easy case	10000	12.93	21.78	12.98	0.0000e+00	2.5847e-11	4.4340e-09
	20000	15.48	25.58	17.00	0.0000e+00	1.0184e-12	9.1688e-11
	30000	21.88	41.75	27.57	0.0000e+00	1.4239e-12	5.7425e-11
	40000	47.51	73.44	54.22	0.0000e+00	4.7311e-11	1.3561e-11
	50000	58.08	98.08	64.23	0.0000e+00	5.0026e-13	1.1820e-11
cond=10							
Hard Case 1	10000	0.83	0.72	0.50	4.5626e-17	2.3592e-14	3.3500e-14
	20000	1.10	1.78	1.18	2.7397e-16	8.3330e-15	1.7622e-14
	30000	3.15	2.30	1.57	3.5323e-16	1.3166e-15	4.6729e-16
	40000	6.33	4.28	3.24	3.8399e-16	1.1407e-15	8.2119e-16
	50000	7.81	4.57	4.61	5.5852e-16	3.1130e-15	5.4845e-15
cond=100							
Hard Case 1	10000	3.26	3.15	3.87	0.0000e+00	1.7803e-13	4.1942e-12
	20000	3.17	6.12	3.35	0.0000e+00	1.5832e-13	2.0746e-12
	30000	6.13	10.74	6.38	0.0000e+00	2.1378e-13	5.6080e-13
	40000	13.63	14.87	11.50	0.0000e+00	6.9402e-14	2.0909e-13
	50000	18.12	16.61	10.89	1.7662e-17	3.3103e-14	1.2959e-14
cond=1000							
Hard Case 1	10000	13.76	26.63	12.61	0.0000e+00	1.5568e-11	5.4200e-09
	20000	15.46	27.88	16.49	0.0000e+00	1.3622e-06	1.3623e-06
	30000	48.37	102.01	49.81	0.0000e+00	2.1438e-12	7.6499e-11
	40000	65.58	105.23	62.84	0.0000e+00	7.4480e-13	6.1595e-11
	50000	80.09	104.03	61.66	0.0000e+00	2.5470e-13	5.6306e-12
cond=10							
Hard Case 2	10000	0.77	2.02	0.98	0.0000e+00	6.3351e-14	2.0440e-11
	20000	1.04	7.51	1.68	0.0000e+00	2.1772e-13	7.9143e-12
	30000	1.87	5.80	2.63	9.0727e-17	5.3708e-14	6.4019e-14
	40000	3.08	26.16	11.26	0.0000e+00	5.2256e-13	3.7264e-12
	50000	4.66	22.71	11.17	0.0000e+00	2.2534e-13	6.8245e-13
cond=100							
Hard Case 2	10000	2.50	16.85	5.48	0.0000e+00	1.6785e-11	1.2714e-08
	20000	3.11	27.54	6.57	0.0000e+00	1.5268e-12	1.8101e-10
	30000	8.96	75.56	16.39	0.0000e+00	8.8052e-12	2.0078e-10
	40000	9.56	89.83	20.02	0.0000e+00	1.6188e-12	3.3824e-10
	50000	18.37	173.57	48.50	0.0000e+00	5.3902e-12	7.1115e-11
cond=1000							
Hard Case 2	10000	18.21	56.16	24.47	0.0000e+00	3.1452e-08	9.3311e-08
	20000	19.76	124.17	38.12	0.0000e+00	7.5228e-09	2.1199e-08
	30000	23.91	222.98	37.13	0.0000e+00	1.4684e-09	4.4186e-09
	40000	46.86	521.06	92.09	0.0000e+00	2.8725e-09	6.5494e-09
	50000	35.38	626.99	91.11	0.0000e+00	5.2262e-10	4.7002e-09

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