

## A MODIFIED ALGORITHM FOR THE STRICT FEASIBILITY PROBLEM

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**Abstract.** In this note, we present a slight modification of an algorithm for the strict feasibility problem. This modification reduces the number of iterations.

**Keywords:** Strict feasibility, interior point methods, Ye–Lustig algorithm.

### 1. INTRODUCTION

This paper is concerned with the problem of finding  $x \in \mathbb{R}^n$  such that

$$x > 0 \quad \text{and} \quad Ax = b \tag{F}$$

where  $A$  is a  $m \times n$  real matrix of rank  $m$ ,  $b \in \mathbb{R}^m$  and  $0 < m < n$ .

This problem, called a *strict feasibility problem*, occurs in many optimization problems in linear or quadratic programming. Such problems are of type

$$\text{Minimize } f(x) \text{ subject to } x \in S = \{x \in \mathbb{R}^n : x \geq 0, Ax = b\}. \tag{P}$$

Let us denote by  $\tilde{S}$  the following subset:

$$\tilde{S} = \{x \in \mathbb{R}^n : x > 0, Ax = b\}.$$

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Interior point methods for solving  $(P)$  start from some arbitrary initial point  $x^0 \in \tilde{S}$  and build a sequence  $\{x^k\} \subset \tilde{S}$  expected to converge to some optimal solution  $x^*$  of  $(P)$ . Thus, the first step in interior point methods consists in finding an initial point  $x^0$  in a efficient way. To do that, it is usual to introduce an artificial variable  $\lambda$  and to consider the linear programming problem

$$\text{Minimize}_{x, \lambda} \{ \lambda : Ax + \lambda(b - Aa^0) = b, x \geq 0, \lambda \geq 0 \} \quad (LF)$$

where  $a^0$  is a arbitrary fixed point in the positive orthant of  $\mathbb{R}^n$ . It is noticed that  $x^*$  is a solution of the feasibility problem  $(F)$  if and only if  $(x^*, 0)$  is an optimal solution of  $(LF)$  with  $x^* > 0$ .

In fact, numerical algorithms provide only approximate optimal solutions for an optimization problem. In our case, an approximate solution of  $(LF)$  can be obtained *via* a classical interior method as for instance the Ye–Lustig algorithm that we described below. But before, we precise the notation used in this algorithm:  $\varepsilon > 0$  corresponds to the precision of the approximation,  $r = \frac{1}{\sqrt{(n+1)(n+2)}}$ ,  $c = (0, 0, \dots, 0, 1)^t \in \mathbb{R}^{n+1}$ ,  $e_{n+2} = (1, 1, \dots, 1)^t \in \mathbb{R}^{n+2}$ ,  $\tilde{x} = (x, \lambda)^t \in \mathbb{R}^{n+1}$  and  $B = [A, b - Aa^0]$  is a  $m \times (n + 1)$  matrix.

## 2. THE ORIGINAL ALGORITHM AND ITS MODIFICATION

Let us describe the original algorithm:

### The Ye–Lustig algorithm [3]

- a) Initialization: start with  $x^0 = a^0$ ,  $\lambda^0 = 1$ ,  $\tilde{x}^0 = (x^0, \lambda^0)^t$  and  $k = 0$ ;  
**If**  $\|Ax^0 - b\| \leq \varepsilon$  **Stop**:  $x^0$  is an  $\varepsilon$ -approximate solution,  
**If not** go to b).
- b) **If**  $\lambda^k \leq \varepsilon$  **Stop**:  $x^k$  is an  $\varepsilon$ -approximate solution,  
**If not** go to c).
- c) Set  $D^k = \text{diag}(\tilde{x}^k)$  and
  - Compute the projection  $p^k$  of the vector  $(D^k c, -c^t \tilde{x}^k)^t \in \mathbb{R}^{n+2}$  on the kernel of the  $m \times (n + 2)$  matrix  $B^k = [BD^k, -b]$ ,
  - Take  $y^{k+1} = \frac{e_{n+2}}{n+2} - \alpha^k r \frac{p^k}{\|p^k\|}$ , where  $\alpha^k$  is obtained by a line search,
  - Take  $\tilde{x}^{k+1} = (x^{k+1}, \lambda^{k+1})^t = (y_{n+2}^{k+1})^{-1} D^k y^{k+1} [n + 1]$ ,
- d) do  $k = k + 1$  and go back to b).

We propose a slight modification of this algorithm by modifying the stopping criteria.

**The modified algorithm**

- a') Initialization: start with  $x^0 = a^0$ ,  $\lambda^0 = 1$ , and  $k = 0$ ;  
**If**  $\|Ax^0 - b\| \leq \varepsilon$  **Stop**:  $x^0$  is an  $\varepsilon$ -approximate solution.  
**If not** compute the solution  $u^0$  of the linear system  
 $AA^t u^0 = \lambda^0(b - Aa^0)$ .
- b') **If**  $\lambda^k \leq \varepsilon$  **Stop**:  $x^k$  is an  $\varepsilon$ -approximate solution.  
**If not**
  - Take  $u^k = \lambda^k u^0$ ,
  - Take  $z^k = -\text{diag}[(x^k)]^{-1} A^t u^k$ ,
  - **If**  $\max|z^k|_i < 1$  **Stop**:  $x^k + A^t u^k$  is an  $\varepsilon$ -approximate solution.  
**If not** go to c')
- c') is identical to c) of the original algorithm.
- d') do  $k = k + 1$  and go back to b').

The computation of the vector  $u^0$  occurs once only, it can be performed by a Cholesky method. It remains to prove the validity of the new stopping criteria  $\max|z^k|_i < 1$ . This is done in the following proposition.

**Proposition 2.1.** *If  $\max|z^k|_i < 1$  then  $x^k + A^t u^k > 0$  and  $A(x^k + A^t u^k) = b$ .*

*Proof.* 1) Notice that  $-\text{diag}(x^k)z^k = A^t u^k$ , then  $x^k + A^t u^k = x^k - \text{diag}(x^k)z^k = \text{diag}(x^k)(e_n - z^k) > 0$  because  $x^k > 0$  and  $|z^k|_i < 1$  for all  $i$ .

2) Since  $(x^k, \lambda^k)^t$  is a feasible solution of  $(LF)$  then  $A(x^k + A^t u^k) = Ax^k + AA^t u^k = b - \lambda^k(b - Aa^0) + \lambda^k AA^t u^0 = b - \lambda^k(b - Aa^0) + \lambda^k \lambda^0(b - Aa^0) = b$ .  $\square$

This modification brings a significant improvement in the number of iterations with only a very small increasing in the cost per iteration. We illustrate that by a few examples.

**3. EXAMPLES**

In this examples  $\varepsilon$  has been taken equal to  $10^{-3}$  or  $10^{-6}$  according to the case.

**3.1. SOME EXAMPLES**

The following examples are taken from the literature see for instance [1, 4]. In particular, Example 7 is called the Hitac problem.

example	taille $m \times n$	Nbr of iterations Ye-Lustig	Nbr of iterations modified algorithm
1	$3 \times 5$	4	1
2	$3 \times 6$	3	1
3	$5 \times 11$	5	4
4	$6 \times 12$	3	1
5	$11 \times 25$	4	3
6	$16 \times 27$	6	5
7	$11 \times 28$	7	6

## 3.2. CUBE EXAMPLE

$n = 2m$ ,  $A[i, j] = 0$  if  $i \neq j$  or  $(i+1) \neq j$   
 $A[i, i] = A[i, i+m] = 1, b[i] = 2$ , for  $i, j = 1 \dots m$ .

Dimension $m \times n$	Nbr of iterations Ye-Lustig	Nbr of iterations Modified algorithm
$50 \times 100$	3	1
$100 \times 200$	3	1
$150 \times 300$	3	1
$200 \times 400$	3	1

## 3.3. HILBERT EXAMPLE

$n = 2m$ ,  $A[i, j] = \frac{1}{i+j}, A[i, i+m] = 1$ ,  
 $b[i] = \sum_{j=1}^m \frac{1}{i+j}$ , for  $i, j = 1 \dots m$ .

Dimension $m \times n$	Nbr of iterations Ye-Lustig	Nbr of iterations Modified algorithm
$50 \times 100$	3	1
$100 \times 200$	3	1
$150 \times 300$	3	1
$200 \times 400$	3	1

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