

A New Iteration-Complexity Bound for  
the MTY Predictor-Corrector Algorithm

*Renato Monteiro (Georgia Tech)*

Takashi Tsuchiya (Inst. of Stat. Math.)

McMaster Univ, Hamilton CA

March 10, 2003

A New Iteration-Complexity Bound for  
the MTY Predictor-Corrector Algorithm

*Renato Monteiro (Georgia Tech)*

Takashi Tsuchiya (Inst. of Stat. Math.)

IMA Workshop on Semidefinite  
Programming and Robust Optimization

March 14, 2003

## TALK OUTLINE

- related works;
- LP problem and assumptions;
- central path and its neighborhood;
- Mizuno-Todd-Ye predictor-corrector (MTY P-C) algorithm;
- condition number and scale-invariance;
- new iteration-complexity bounds for finding;
  - a near optimal solution;
  - an exact optimal solution (with the use of a scaling-invariant FT procedure);
- brief outline of our analysis;
- concluding remarks.

## RELATED WORKS

The **Vavasis-Ye layered-step** method is an interior-point method for solving the LP problem  $\min\{c^T x : Ax = b, x \geq 0\}$ , where  $A \in \mathbb{R}^{m \times n}$ . Using the notion of **crossover events**, they showed that their algorithm has an iteration-complexity which depends neither on  $b$  nor  $c$ , namely

$$\mathcal{O}(n^{3.5} \log(\bar{\chi}_A + n)),$$

where  $\bar{\chi}_A$  is a condition number for  $A$ . ( $\bar{\chi}_A$  is known to be  $2^{L_A}$ , where  $L_A$  is the input size of  $A$ .) In addition to the ordinary steps of path following IPMs, their algorithm uses **layered least squares (LLS)** steps from time to time.

One **drawback** of their algorithm is that an estimate of  $\bar{\chi}_A$ , which is very difficult to obtain, is needed for computing the LLS step.

**Megiddo, Mizuno and Tsuchiya** (Math Progr 98) and **Monteiro and Tsuchiya** (SIOPT) have proposed distinct ways to get around this problem.

## RELATED WORKS (CONTINUED)

The Mizuno-Todd-Ye (MTY) predictor-corrector (P-C) algorithm is a popular and theoretically appealing method which converges both **polynomially** and **quadratically**.

Using the notion of crossover events too, we derive a **new iteration-complexity bound** for the MTY P-C algorithm in terms of the condition number  $\bar{\chi}_A$ .

The new iteration complexity bound is **scaling invariant**, and becomes

$$\mathcal{O}(n^{3.5} L_A + n^2 \log L)$$

under the Turing Machine Model, where  $L$  is the input size of  $(A, b, c)$  and  $n$  is the number of variables. This contrasts strongly with the best classical bound of  $\mathcal{O}(\sqrt{n} L)$ , which is proportional to  $L$  instead of  $\log L$ .

## THE LP PROBLEM

$$\begin{aligned} (P) \quad & \text{minimize}_x \quad c^T x \\ & \text{subject to} \quad Ax = b, \quad x \geq 0, \end{aligned}$$

$$\begin{aligned} (D) \quad & \text{maximize}_{(y,s)} \quad b^T y \\ & \text{subject to} \quad A^T y + s = c, \quad s \geq 0, \end{aligned}$$

### Assumptions

- 1)  $(P)$  and  $(D)$  have interior-feasible solutions.
- 2) the rows of the  $m \times n$  matrix  $A$  are linearly independent.

**Definition** The **duality gap** of a feasible  $(x, y, s)$  is given by

$$c^T x - b^T y = (A^T y + s)^T x - b^T y = x^T s.$$

## CENTRAL PATH AND ITS NEIGHBORHOOD

For each  $\nu > 0$ , the system

$$\begin{aligned} X S e &= \nu e, \\ A x - b &= 0, \quad (x, s) \geq 0, \\ A^T y + s - c &= 0, \end{aligned}$$

where  $X = \text{Diag}(x)$ ,  $S = \text{Diag}(s)$  and  $e = (1, \dots, 1)^T$ , has a unique solution  $(x(\nu), y(\nu), s(\nu))$ , which converges to a primal-dual optimal solution as  $\nu \rightarrow 0$ .

The MTY P-C is based on the 2-norm neighborhood of the central path:

$$\mathcal{N}(\beta) \equiv \{(x, y, s) \text{ feasible} : \|X s - \mu e\| \leq \beta \mu\},$$

where  $\mu = \mu(x, s) \equiv (x^T s)/n$  and  $\beta$  is a positive constant.

## MTY P-C ALGORITHM

**Search directions:** For a feasible  $(x, y, s)$ , the Newton direction towards the point  $(x(\nu), y(\nu), s(\nu))$  is obtained by solving the linear system:

$$\begin{aligned} X\Delta s + S\Delta x &= -Xs + \nu e, \\ A\Delta x &= 0, \\ A^T \Delta y + \Delta s &= 0 \end{aligned}$$

Setting  $\nu = 0$  yields the predictor (or affine scaling) direction at  $(x, y, s)$ . This direction aims towards an optimal solution of  $(P)$  and  $(D)$ .

Setting  $\nu = \mu(x, s)$  yields the corrector (or centrality) direction at  $(x, y, s)$ . This direction aims towards the point on the central-path having the same duality gap as the current point  $(x, y, s)$ .

## AN ITERATION OF THE MTY P-C ALG.

Let  $w = (x, y, s) \in \mathcal{N}(\beta)$  be given, where  $\beta \in (0, 1/4]$ .

- 1) Compute the AS direction  $\Delta w^a = (\Delta x^a, \Delta y^a, \Delta s^a)$  at  $w$ ;
- 2) Let  $\alpha_p > 0$  be the maximum  $\alpha \in [0, 1]$  such that  $w + \alpha \Delta w^a \in \mathcal{N}(2\beta)$ ;
- 3) Set  $w_p = w + \alpha_p \Delta w^a$ ;
- 4) Compute the corrector direction  $\Delta w^c = (\Delta x^c, \Delta y^c, \Delta s^c)$  at  $w_p$ ;
- 5) The next point  $w^+$  is determined as  $w^+ = w_p + \Delta w^c$ ;

It can be proved that  $w^+ \in \mathcal{N}(\beta)$ . Hence, a new iteration can be started by setting  $w \leftarrow w^+$  and going back to 1).

## CLASSICAL CONVERGENCE RESULTS

**Lemma:** Suppose  $w = (x, y, s) \in \mathcal{N}(\beta)$ , where  $\beta \in (0, 1/4]$ . Then,  $w^+ \in \mathcal{N}(\beta)$  and

$$\frac{\mu(w^+)}{\mu(w)} \leq \min \left\{ 1 - \sqrt{\frac{\beta}{n}}, \frac{\varepsilon_\infty^a \sqrt{n}}{\beta} \right\},$$

where  $\delta = s^{1/2}x^{-1/2}$  and

$$\varepsilon_\infty^a \equiv \max_i \left\{ \min \left\{ \left| \frac{\delta_i^{-1} \Delta s_i^a}{\sqrt{\mu}} \right|, \left| \frac{\delta_i \Delta x_i^a}{\sqrt{\mu}} \right| \right\} \right\}.$$

**Consequences:**

- The first bound implies that the MTY algorithm converges **polynomially**, namely in  $\mathcal{O}(\sqrt{n}L)$  iterations under the TMM.
- Since  $\varepsilon_\infty^a = \mathcal{O}(\mu(w))$  asymptotically, the second bound implies that  $\mu(w^+) = \mathcal{O}(\mu(w)^2)$ . This implies that the MTY algorithm converges **quadratically**.

## THE CONDITION NUMBER $\bar{\chi}_A$

Define

$$\bar{\chi}_A \equiv \sup\{\|(ADA^T)^{-1}AD\| : D \in \mathcal{D}\},$$

where  $\mathcal{D}$  denotes the set of all positive definite diagonal matrices.

Facts:

- 1) if  $A$  integral then  $\bar{\chi}_A \leq 2^{L_A}$ , where  $L_A$  is the input size of  $A$ .
- 2) Finding an upper bound for  $\bar{\chi}_A$  is a  $\mathcal{NP}$  hard problem.
- 3)  $\bar{\chi}_A = \max\{\|A_B^{-1}A\| : A_B \text{ is a basis of } A\}$ .

## SCALE INVARIANCE

Let  $D$  be a positive diagonal matrix and consider the pair of LPs:

$$\begin{aligned} (\tilde{P}) \quad & \text{minimize}_{\tilde{x}} && (Dc)^T \tilde{x} \\ & \text{subject to} && AD\tilde{x} = b, \tilde{x} \geq 0, \end{aligned}$$

$$\begin{aligned} (\tilde{D}) \quad & \text{maximize}_{(\tilde{y}, \tilde{s})} && b^T \tilde{y} \\ & \text{subject to} && DA^T \tilde{y} + \tilde{s} = \tilde{c}, \tilde{s} \geq 0, \end{aligned}$$

obtained from  $(P)$  and  $(D)$  by performing the change of variables  $(x, y, s) = \Phi(\tilde{x}, \tilde{y}, \tilde{s}) \equiv (D\tilde{x}, \tilde{y}, D^{-1}\tilde{s})$ .

The MTY P-C algorithm is **scaling-invariant**, i.e., if  $\{w^k\}$  and  $\{\tilde{w}^k\}$  denote the sequence of iterates generated by the MTY P-C algorithm in the original and the scaled space, then  $w^k = \Phi(\tilde{w}^k)$  for all  $k \geq 1$ , as long as the initial iterates satisfy this relation too, that is  $w^0 = \Phi(\tilde{w}^0)$ .

**Remark:** Vavasis-Ye algorithm and its variants are not scaling invariant.

## NEW COMPLEXITY RESULTS

**Theorem 1:** Given  $\eta > 0$  and an initial point  $w^0 \in \mathcal{N}(\beta)$ , with  $\beta \in (0, 1/4]$ , the MTY P-C algorithm generates an iterate  $w^k \in \mathcal{N}(\beta)$  satisfying  $\mu(w^k) \leq \eta$  in at most

$$\mathcal{O} \left( \min \left( \begin{array}{c} \sqrt{n} \log(\mu_0/\eta) \\ n^2 \log(\log(\mu_0/\eta)) + n^{3.5} \log(\bar{\chi}_A^* + n) \end{array} \right) \right)$$

iterations, where  $\mu_0 \equiv \mu(w^0)$  and

$$\bar{\chi}_A^* \equiv \inf\{\bar{\chi}_{AD} : D \in \mathcal{D}\}.$$

**Remark:**  $\bar{\chi}_A^*$  is a scaling invariant condition number of  $A$ .

## FINITE TERMINATION PROCEDURE

Given a feasible point  $w = (x, y, s)$ , it consists of two steps:

- determine a guess  $(B(w), N(w))$  for the optimal partition  $(B_*, N_*)$  defined as

$$B_* \equiv \{i : x_i^* > 0 \text{ for some } x^* \in \text{opt}(P)\},$$

$$N_* \equiv \{i : s_i^* > 0 \text{ for some } (y^*, s^*) \in \text{opt}(D)\}.$$

- “project”  $w$  onto the “manifold” determined by  $(B(w), N(w))$ .

The partition  $(B, N) = (B(w), N(w))$  is found as

$$B = \left\{ i : \left| \frac{\delta_i \Delta x_i^a}{\sqrt{\mu}} \right| \leq \left| \frac{\delta_i^{-1} \Delta s_i^a}{\sqrt{\mu}} \right| \right\},$$

$$N = \{1, \dots, n\} \setminus B,$$

where  $\delta \equiv s^{1/2} x^{-1/2}$ .

**Remark:** This partition is scaling-invariant.

Next, we solve the following projection problems:

$$\begin{aligned}
 x^* &\equiv \operatorname{argmin}_{\tilde{x}} \{ \|\delta(x - \tilde{x})\|^2 : A\tilde{x} = b, \tilde{x}_N = 0 \}, \\
 (y^*, s^*) &\equiv \operatorname{argmin}_{(\tilde{y}, \tilde{s})} \left\{ \|\delta^{-1}(s - \tilde{s})\|^2 : \begin{array}{l} A^T \tilde{y} + \tilde{s} = c \\ \tilde{s}_B = 0 \end{array} \right\}.
 \end{aligned}$$

If  $x_B^* > 0$  and  $s_N^* > 0$  then  $w^* = (x^*, y^*, s^*)$  is a strictly complementary optimal solution; output  $w^*$  and declare **success**. Otherwise, exit the procedure and declare **failure**.

**Proposition:** There exists a scaling invariant constant  $\eta_* > 0$  such that the above FT Procedure always succeeds whenever  $\mu(w) \leq \eta_*$ .

**Theorem 2:** Suppose  $w^0 \in \mathcal{N}(\beta)$ , where  $\beta \in (0, 1/4]$ . Then, the MTY P-C algorithm with the above FT Procedure started from  $w^0$  finds a primal-dual strictly complementary optimal solution  $w^*$  in at most

$$\mathcal{O} \left( \min \left\{ \begin{array}{c} \sqrt{n} \log(n\mu_0/\eta_*) \\ n^2 \log(\log(n\mu_0/\eta_*)) + n^{3.5} \log(\bar{\chi}_A^* + n) \end{array} \right\} \right)$$

iterations, where  $\mu_0 = \mu(w^0)$ , and

$$\eta_* \equiv \sup \left\{ \frac{[\xi(AD, b, Dc)]^2}{\zeta(AD, (B_*, N_*))} : D \in \mathcal{D} \right\}.$$

By definition,  $\xi(A, b, c) \equiv \min \{ \min_{i \in B_*} \xi_i^P, \min_{i \in N_*} \xi_i^D \}$ , where for every  $i = 1, \dots, n$ ,

$$\begin{aligned} \xi_i^P &\equiv \max\{\bar{x}_i : \bar{x} \text{ optimal for (P)}\}, \\ \xi_i^D &\equiv \max\{\bar{s}_i : (\bar{y}, \bar{s}) \text{ optimal for (D)}\}. \end{aligned}$$

Also,  $\zeta(A, (B_*, N_*)) \equiv \max\{\zeta_P, \zeta_D\}$ , where

$$\begin{aligned} \zeta_P &\equiv \max_{d_{N_*} \neq 0} \left\{ \min \left\{ \frac{\|d_{B_*}\|}{\|d_{N_*}\|} : d = (d_{B_*}, d_{N_*}) \in \text{Ker}(A) \right\} \right\}, \\ \zeta_D &\equiv \max_{d_{B_*} \neq 0} \left\{ \min \left\{ \frac{\|d_{N_*}\|}{\|d_{B_*}\|} : d = (d_{B_*}, d_{N_*}) \in \text{Im}(A^T) \right\} \right\}. \end{aligned}$$

## COMPLEXITY BOUNDS UNDER THE TMM

Assume that the data  $(A, b, c)$  is integral. Let  $L$  and  $L_A$  denote the input size of  $(A, b, c)$  and  $A$ , respectively.

Using the big M idea, Vavasis and Ye constructed an auxiliary pair of LP problems with the following properties:

- i) the input size of its coefficient matrix is bounded by  $\mathcal{O}(L_A)$ ;
- ii) its cost and right hand coefficients are bounded by  $\mathcal{O}(L)$ ;
- iii) it admits a readily available well-centered initial point whose duality gap is  $n 2^{\mathcal{O}(L)}$ , and;
- iv) if  $(P)$  and  $(D)$  have an optimal solution, then such a solution can be easily obtained from an optimal solution of the auxiliary pair of LPs.

**Theorem 3:** Suppose that  $(P)$  and  $(D)$  have a primal-dual optimal solution. Then, the MTY P-C algorithm together with the FT Procedure applied to the above auxiliary pair of LP problems, finds a strictly complementary primal-dual optimal solution of  $(P)$  and  $(D)$  in

$$\mathcal{O} \left( \min \left\{ \sqrt{n} L, n^2 \log L + n^{3.5} (L_A + \log n) \right\} \right)$$

iterations.

## BRIEF ANALYSIS OUTLINE

**Definition (Vavasis and Ye):** For a constant  $\mathcal{C} \geq 1$ , a  $\mathcal{C}$ -crossover event is said to occur on the interval  $(\nu_1, \nu_2]$  if there exists indices  $i, j \in \{1, \dots, n\}$  such that

$$s_j(\nu_2) \leq \mathcal{C} s_i(\nu_2), \text{ and}$$

$$s_j(\nu) > \mathcal{C} s_i(\nu) \text{ for all } \nu \leq \nu_1.$$

**Proposition:** For any fixed  $\mathcal{C} \geq 1$ , there exists at most  $n(n-1)/2$  disjoint intervals of the form  $(\nu_1, \nu_2]$  containing  $\mathcal{C}$ -crossover events.

.

- Basic result of Vavasis and Ye on the relationship between LLS steps and crossover events.
- Proximity result between the primal-dual affine scaling direction and LLS steps;
- A new partition introduced by Monteiro and Tsuchiya;
- Realization that the MTY P-C algorithm at times (i.e.,  $\mathcal{O}(n^2)$  times) behaves quadratically convergent.



There exists  $\mathcal{C} > 0$  such that a  $\mathcal{C}$ -crossover event occurs every

$$\mathcal{O}(\log(\log(\mu_0/\eta)) + n^{1.5} \log(\bar{\chi}_A + n))$$

iterations. Since there are at most  $\mathcal{O}(n^2)$  disjoint  $\mathcal{C}$ -crossover events, the MTY P-C algorithm terminates in

$$\mathcal{O}(n^2 \log(\log(\mu_0/\eta)) + n^{3.5} \log(\bar{\chi}_A + n)).$$

## CONCLUDING REMARKS

We have presented a new iteration-complexity bound for the MTY P-C algorithm obtained by means of the notion of crossover events.

Possible [open problems](#) are:

- Can a general pair of LP problems be solved by the MTY P-C algorithm with the same complexity derived in this paper under the real-computation model?
- Is there an alternative notion that can be used in place of crossover event which, instead of the latter, is scaling-invariant?
- Can an iteration-complexity bound depending only on  $n$  and  $\bar{\chi}_A^*$  be derived for the MTY P-C algorithm?