Some ≥ew Path-Following Algorithms for Convex Quadratic Programming

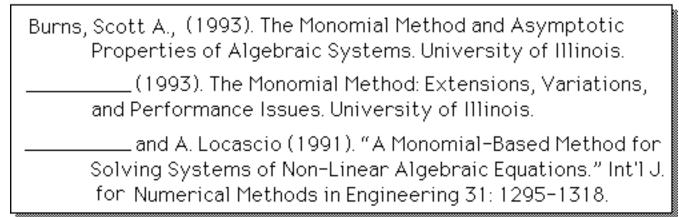
Dennis L. Bricker & Yi-Chih Hsieh Dept. of Industrial Engineering University of Iowa stmt. of the QP problem

In path-following methods for convex quadratic programming, one must solve systems of equations of the form:

$$\begin{cases} Ax - y = b \\ -Qx + A^{T}w + s = c \\ XSe = \mu e \\ WYe = \mu e \end{cases}$$

This system consists of both linear and nonlinear equations, and are frequently solved using Newton's method.

The motivation for our current work was a presentation by Scott Burns (U. of Illinois) on the "Monomial Method" for solving certain systems of nonlinear equations.



- Arithmetic-Geometric Mean Inequality
- Condensation of Posynomials
- Posynomial Approximation of Signomials
- The "Monomial Method" for Solving Systems of Nonlinear Equations
- 📭 A "toy" LCP Example
- Application to Path-Following Algorithm
- 🕼 Computational Experience

Simplest case: Given two positive numbers a&b,

their arithmetic mean $\frac{1}{2}a + \frac{1}{2}b$ is greater than or equal to their geometric mean \sqrt{ab}

i.e.,
$$\frac{1}{2} a + \frac{1}{2} b \ge a^{\frac{1}{2}} b^{\frac{1}{2}}$$

with equality if & only if a = b

$$\frac{1}{2} a + \frac{1}{2} b \ge a^{\frac{1}{2}} b^{\frac{1}{2}}$$

For example, let a=2 & b=8. Then this inequality is

$$5 = \frac{1}{2} \times 2 + \frac{1}{2} \times 8 \ge \sqrt{2 \times 8} = 4$$
Arithmetic mean Geometric Mean

If a=4 & b=9,

$$6.5 = \frac{1}{2} \times 4 + \frac{1}{2} \times 9 \ge \sqrt{4 \times 9} = 6$$
Arithmetic mean Geometric Mean

$$\frac{1}{2} a + \frac{1}{2} b \ge a^{\frac{1}{2}} b^{\frac{1}{2}}$$

Proof:

Let
$$\alpha \& \beta$$
 be real numbers

and $a = \alpha^2 \ge 0$

$$b = \beta^2 \ge 0$$

Then
$$(\alpha - \beta)^2 = \alpha^2 - 2\alpha\beta + \beta^2 \ge 0$$

$$\Rightarrow \alpha^2 + \beta^2 \ge 2\alpha\beta$$

$$\Rightarrow \frac{1}{2}\alpha^2 + \frac{1}{2}\beta^2 \ge \alpha\beta \Rightarrow \frac{1}{2}a + \frac{1}{2}b \ge \sqrt{ab}$$

The General Case: Let
$$x_1$$
, x_2 , ... $x_n > 0$ and δ_1 , δ_2 , ... $\delta_n \geq 0$ and $\sum_{i=1}^n \delta_i = 1$ Then
$$\sum_{i=1}^n \delta_i |x_i| \geq \prod_{i=1}^n x_i^{\delta_i}$$

with equality if & only if $X_1 = X_2 = ... = X_n$

$$\sum_{i=1}^{n} \delta_{i} x_{i} \geq \prod_{i=1}^{n} x_{i}^{\delta_{i}}$$

If we let n=2, and δ_i = $\frac{1}{2}$, then we obtain the earlier inequality,

$$\frac{1}{2} a + \frac{1}{2} b \ge a^{\frac{1}{2}} b^{\frac{1}{2}}$$

Writing $\mathbf{u}_i \equiv \mathbf{\delta}_i \mathbf{x}_i$, we get

$$\begin{array}{c|c} \textit{Equivalent} & \sum_i \ \mathbf{u}_i \geq \prod_i \ \left(\!\!\!\begin{array}{c} \mathbf{u}_i \!\!\!/ \!\!\! \delta_i \end{array}\!\!\!\right)^{\delta_i} \end{array}$$

where
$$\delta_1$$
, δ_2 , ... $\delta_n \geq 0$ and $\sum_{i=1}^n \delta_i = 1$ with equality if & only if $u_1/\delta_1 = u_2/\delta_2 = \ldots = u_n/\delta_n$

Condensation of Posynomials

$$g(x_1, x_2, \dots x_m) = \sum_{i=1}^n c_i \prod_{j=1}^m x_j^{a_{ij}}$$

where $c_i > 0$ and a_{ij} are real numbers.

Recall the A-G Mean Inequality:

Letting
$$\mathbf{u}_i = \mathbf{c}_i \prod_j \mathbf{x}_j^{a_{ij}}$$
, we obtain

$$\mathbf{g}(\mathbf{x}) = \sum_{i} \ \mathbf{c}_{i} \ \prod_{j} \ \mathbf{x}_{j}^{a_{ij}} \geq \prod_{i} \left[\frac{\mathbf{c}_{i} \ \prod_{j} \ \mathbf{x}_{j}^{a_{ij}}}{\delta_{i}} \right]^{\delta_{i}} = C(\delta) \prod_{j} \ \mathbf{x}_{j}^{\alpha_{ij}(\delta)}$$

where
$$C(\delta) = \prod_{i} \left(\frac{c_i}{\delta_i}\right)^{\delta_i}, \alpha_j(\delta) = \sum_{i} a_{ij}\delta_i$$

That is, we obtain a monomial approximation (lower bound) of the posynomial,

$$g(x) = \sum_{i} c_{i} \prod_{j} x_{j}^{a_{ij}} \ge C(\delta) \prod_{j} x_{j}^{\alpha_{ij}(\delta)}$$

where
$$C(\delta) = \prod_i \left(\frac{\mathbf{c}_i}{\delta_i}\right)^{\delta_i}, \, \alpha_j(\delta) = \sum_i a_{ij}\delta_i$$

which is exact when

$$\frac{\mathbf{c}_1 \prod_j \mathbf{x}_j^{a_{1j}}}{\delta_1} = \frac{\mathbf{c}_2 \prod_j \mathbf{x}_j^{a_{2j}}}{\delta_2} = \cdots = \frac{\mathbf{c}_n \prod_j \mathbf{x}_j^{a_{nj}}}{\delta_n}$$

Signomial Functions

coefficients not restricted in sign!

$$g(x_1, x_2, \dots x_m) = \sum_{i=1}^{n} c_i \prod_{j=1}^{m} x_j^{a_{ij}}$$

Condensation has long been used in solving Signomial GP problems (which are essentially nonconvex) by means of a sequence of approximating Posynomial GP problems (which are essentially convex problems).



Example

Minimize x_1 subject to

$$(x_1-2)^2 + (x_2-4)^2 \ge 4 \leftarrow$$

X is outside a circle

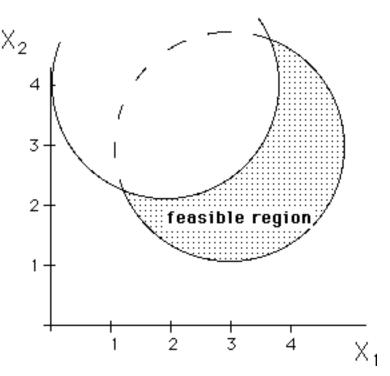
radius 2

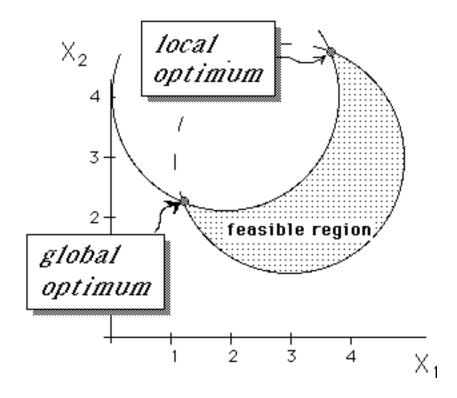
Minimize x₁ subject to

$$(x_1-2)^2 + (x_2-4)^2 \ge 4$$

$$(x_1-2)^2 + (x_2-4)^2 \ge 4$$

 $(x_1-3)^2 + (x_2-3)^2 \le 4$





Reformulation as a GP problem

$$(X_{1}-2)^{2} + (X_{2}-4)^{2} \ge 4$$

$$\Rightarrow (x_{1}^{2}-4x_{1}+4) + (x_{2}^{2}-8x_{2}+16) \ge 4$$

$$\Rightarrow -x_{1}^{2}+4x_{1}-x_{2}^{2}+8x_{1} \le 16$$

The constraint becomes the signomial constraint

$$\Rightarrow \frac{X_1}{4} + \frac{X_2}{2} - \frac{X_1^2}{16} - \frac{X_2^2}{16} \le 1$$

Reformulation as a GP problem

$$(X_1 - 3)^2 + (X_2 - 3)^2 \le 4$$

$$\Rightarrow (x_1^2 - 6x_1 + 9) + (x_2^2 - 6x_2 + 9) \le 4$$

$$\Rightarrow x_1^2 - 6x_1 + x_2^2 + 14 \le 6x_2$$

The constraint becomes the signomial constraint

$$\Rightarrow \frac{X_1^2 X_2^{-1}}{6} + \frac{X_2}{6} + \frac{7X_2^{-1}}{3} - X_1 X_2^{-1} \le 1$$

Signomial Geometric Program

Minimize X₁ subject to

$$\begin{split} &\frac{X_1}{4} + \frac{X_2}{2} - \frac{X_1^2}{16} - \frac{X_2^2}{16} \le 1 \\ &\frac{X_1^2 X_2^{-1}}{6} + \frac{X_2}{6} + \frac{7X_2^{-1}}{3} - X_1 X_2^{-1} \le 1 \\ &X_1 > 0, \ X_2 > 0 \end{split}$$

To condense the signomial constraint

$$\frac{X_1}{4} + \frac{X_2}{2} - \frac{X_1^2}{16} - \frac{X_2^2}{16} \le 1$$

we first write it in the form

$$\frac{X_1}{4} + \frac{X_2}{2} \le 1 + \frac{X_1^2}{16} + \frac{X_2^2}{16}$$

$$\Rightarrow \frac{\frac{X_1}{4} + \frac{X_2}{2}}{1 + \frac{X_1^2}{16} + \frac{X_2^2}{16}} \le 1 \Rightarrow \frac{0.25X_1 + 0.5X_2}{1 + 0.0625 X_1^2 + 0.0625 X_2^2} \le 1$$

We next condense the denominator of

$$\frac{0.25X_1 + 0.5X_2}{1 + 0.0625 X_1^2 + 0.0625 X_2^2} \le 1$$

into a single term. Let's use the point $X_0 = (4,5)$ at which the terms of the denominator are

$$1 + 1 + 1.5626 = 3.5625$$

Then

$$\delta_1 = \delta_2 = \frac{1}{3.5625} = 0.2807$$
 and $\delta_3 = \frac{1.5625}{3.5625} = 0.4386$

$$\delta_1 = \delta_2 = 0.2807, \quad \delta_3 = 0.4386$$

Coefficient:

$$\mathbf{C}(\delta) = \prod_{i=1}^{3} \left(\frac{\mathbf{c}_{i}}{\delta_{i}}\right)^{\delta_{i}}$$

$$C(\delta) = \left(\frac{1}{0.2807}\right)^{0.2807} \left(\frac{0.0625}{0.2807}\right)^{0.2807} \left(\frac{0.0625}{0.4386}\right)^{0.4386}$$
$$= 0.3987$$

$$\delta_1 = \delta_2 = 0.2807, \quad \delta_3 = 0.4386$$

$$\mathbf{a}_{j}\left(\delta\right) = \sum_{i=1}^{3} \mathbf{a}_{ij} \delta_{i}$$

$$a_1=0\delta_1+2\delta_2+0\delta_3=2(0.2807)=0.5614$$

$$a_2 = 0\delta_1 + 0\delta_2 + 2\delta_3 = 2(0.4386) = 0.8772$$

$$C(\delta) = 0.3987$$
 $a_1 = 0.5614$
 $a_2 = 0.8772$

Condensed denominator is

 $0.3987 X_1^{0.5614} X_2^{0.8772}$

monomial!

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Geometric Inequality implies

$$1 + 0.0625X_1^2 + 0.0625X_2^2 \ge 0.3987X_1^{0.5614}X_2^{0.8772}$$

and so

$$\frac{0.25X_1 + 0.5X_2}{1 + 0.0625 \; \text{χ}_1^2 + 0.0625 \; \text{χ}_2^2} \leq \frac{0.25X_1 + 0.5X_2}{0.3987 \; \text{χ}_1^{0.5614} \; \text{χ}_2^{0.8772}}$$

$$\frac{0.25X_1 + 0.5X_2}{0.3987 X_1^{0.5614} X_2^{0.8772}}$$

$$= \frac{0.25}{0.3987} \, X_{1}^{\text{1-0.5614}} \, X_{2}^{\text{-0.8772}} + \frac{0.5}{0.3987} \, X_{1}^{\text{-0.5614}} \, X_{2}^{\text{1-0.8772}}$$

=
$$0.627 X_1^{0.4386} X_2^{-0.8772} + 1.254 X_1^{-0.5614} X_2^{0.1228}$$

which is a posynomial!

If we constrain this posynomial so as to be ≤ 1 , then by the geometric inequality, the original signomial should also be ≤ 1 .

That is, any X feasible in the posynomial constraint derived by condensation will also be feasible in the signomial constraint:

$$\frac{0.25X_1 + 0.5X_2}{1 + 0.0625 X_1^2 + 0.0625 X_2^2}$$

$$\leq 0.627 X_1^{0.4386} X_2^{-0.8772} + 1.254 X_1^{-0.5614} X_2^{0.1228} \leq 1$$

The second signomial constraint may be condensed in a similar fashion:

$$\frac{X_{1}^{2}X_{2}^{-1}}{6} + \frac{X_{2}}{6} + \frac{7X_{2}^{-1}}{3} - X_{1}X_{2}^{-1} \le 1$$

$$\implies \frac{X_{1}^{2}X_{2}^{-1}}{6} + \frac{X_{2}}{6} + \frac{7X_{2}^{-1}}{3} \le 1 + X_{1}X_{2}^{-1}$$

$$\implies \frac{X_{1}^{2}X_{2}^{-1}}{6} + \frac{X_{2}}{6} + \frac{7X_{2}^{-1}}{3} \le 1$$

$$\implies \frac{1 + X_{1}X_{2}^{-1}}{6} \le 1$$

$$\frac{X_1^2 X_2^{-1}}{6} + \frac{X_2}{6} + \frac{7X_2^{-1}}{3}$$

$$\leq 1$$
At (4,5), the denominator is 1 + 0.8 = 1.8, so
$$\delta_1 = \frac{1}{1 - 0.555}, \delta_2 = \frac{0.8}{1 - 0.44}$$

$$\delta_1 = \frac{1}{1.8} = 0.555, \ \delta_2 = \frac{0.8}{1.8} = 0.444$$

can be condensed (using $\delta_1 = 0.555$, $\delta_2 = 0.444$) into the posynomial constraint

$$0.08385 X_{1}^{1.555} X_{2}^{-0.555} + 0.08385 X_{1}^{-0.444} X_{2}^{1.444} + 1.174 X_{1}^{-0.444} X_{2}^{-0.555} \leq 1$$

The signomial GP problem is therefore approximated by the posynomial problem:

Minimize X₁ subject to

$$0.627 X_1^{0.4386} X_2^{-0.8772} + 1.254 X_1^{-0.5614} X_2^{0.1228} \le 1$$

$$0.08385X_{1}^{1.555}X_{2}^{-0.555} + 0.08385X_{1}^{-0.444}X_{2}^{1.444} + 1.174X_{1}^{-0.444}X_{2}^{-0.555} \le 1$$

$$X_{1} > 0, X_{2} > 0$$



Monomial Method We wish to find a *(positive)* solution of the following system of nonlinear (signomial) equations:

$$\begin{aligned} g_k(x) &= \sum_i \ \sigma_{ik} \mathbf{c}_{ik} \prod_j \ x_j^{a_{ijk}} = 0 , \ k=1 , \cdots N \\ & \text{where} \quad \sigma_{ik} \in \{+1, -1\}, \quad \mathbf{c}_{ik} > 0 \\ & Example: \quad \begin{cases} 2.5 \ x_1^{-1.5} + 15 \ x_1^{8/3} x_2^{-2} - 30 x_2 = 0 \\ 77 + 9 \ x_2^{-1} - 28 x_1 x_2 - 4 x_1^{-3} = 0 \end{cases} \end{aligned}$$

Define the index sets of the positive & negative terms of each equation:

$$T_k^+ = \{ i \mid \sigma_{ik} > 0 \} \& T_k^- = \{ i \mid \sigma_{ik} < 0 \}$$

Then separate each signomial into positive & negative parts:

$$\mathbf{g}_{k}(\mathbf{x}) = \mathbf{P}_{k}(\mathbf{x}) - \mathbf{Q}_{k}(\mathbf{x})$$

where

$$P_k(x) = \sum_{i \in T_k^+} \mathbf{c}_{ik} \prod_j \ x_j^{a_{ijk}} \ \& \ Q_k(x) = \sum_{i \in T_k^-} \mathbf{c}_{ik} \prod_j \ x_j^{a_{ijk}}$$

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$$g_k(x) = P_k(x) - Q_k(x) = 0$$

$$\Rightarrow P_k(x) = Q_k(x)$$

$$\Rightarrow \frac{P_k(x)}{Q_k(x)} = 1$$

Each of the posynomials $P_k(x)$ and $Q_k(x)$ are then condensed into monomial approximations $\overline{P}_k(x)$ and $\overline{Q}_k(x)$, respectively, and the ratio of the two monomials is also a monomial!

Each nonlinear equation is then approximated by a monomial equation

$$\frac{P_k(x)}{Q_k(x)} \approx \ \frac{\overline{P}_k(x)}{\overline{Q}_k(x)} = C_k(\delta) \prod_j x_j^{\alpha_{jk}(\delta)} \!\!\! = 1$$

for some choice of the weights (δ)

By taking the logarithms of both sides and making the change of variable $z_j = \ln x_j$

we get the linear equation

$$\sum_{j} \alpha_{jk}(\delta) \ \mathbf{z}_{j} = - \mathbf{C}_{k}(\delta)$$

- Select an initial starting point x°.
- 1 Evaluate the weights of all the terms:

$$\delta_{ik} = \frac{\mathbf{c}_{ik} \prod\limits_{j} (x^{\diamond})_{j}^{a_{ijk}}}{P_{k}(x^{\diamond})} \ \forall \ i \in T_{k}^{+} \ \& \ \delta_{ik} = \frac{\mathbf{c}_{ik} \prod\limits_{j} (x^{\diamond})_{j}^{a_{ijk}}}{Q_{k}(x^{\diamond})} \ \forall \ i \in T_{k}^{-}$$

- 2 Evaluate $C_k(\delta)$ and $\alpha_{kj}(\delta)$
- 3 Solve the linear system of equations in z.
- 4 Exponentiate z to obtain x' (yielding x' > 0!)
- 5 Test for convergence, e.g.,

$$\|x^{\diamond} - x'\| \leq \varepsilon$$

If the test fails, replace x° with x' and return to step 1.

It can be shown that the "Monomial" Method is equivalent to Newton's Method applied to

$$\ln \left[\frac{P_k(e^x)}{Q_k(e^x)} \right] = 0, \quad k=1,...N$$

Standard Newton

$$P(x) - Q(x) = 0$$

Newton-Central $P(e^z) - Q(e^z) = 0$

$$P(e^{z}) - Q(e^{z}) = 0$$

$$\frac{P(e^2)}{O(e^2)} = 1$$

Monomial |

$$\ln \left| \frac{P(e^2)}{O(e^2)} \right| = 0$$

These all have the property that they will exactly follow the central path and yield strictly positive iterates!



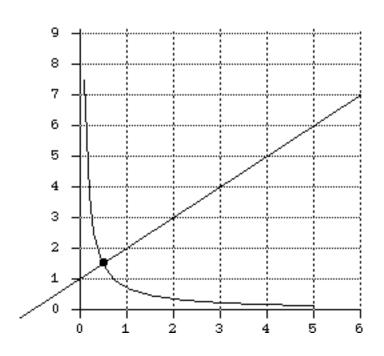
Example

A "toy" $\angle CP$: $y = Mx + q, \ xy = 0$

$$\begin{cases} xy = \mu \\ y = x + 1 \end{cases}$$

i.e., one "complementarity" equation one linear equation





$$\begin{cases} xy = \mu = 0.75 \\ y = x + 1 \end{cases}$$

In general, the solution is

$$x(\mu) = -\frac{1}{2} + \sqrt{\frac{1}{4} + \mu}$$

 $y(\mu) = \frac{1}{2} + \sqrt{\frac{1}{4} + \mu}$

Monomial Method Note that the "complementarity" equation is already in monomial form.

The linear equation is approximated by a monomial as follows: P - Q = (x+1) - y = 0

$$\Rightarrow \frac{P}{Q} = \frac{x+1}{y} = 1$$

$$|\mathbf{x}| + |\mathbf{1}| \ge \left(\frac{\mathbf{x}}{\delta_1}\right)^{\delta_1} \left(\frac{\mathbf{1}}{\delta_2}\right)^{\delta_2} = \delta_1^{-\delta_1} \delta_2^{-\delta_2} \mathbf{x}^{\delta_1}$$

where the weights are:

$$\delta_1 = \frac{\mathbf{x}^{\diamond}}{\mathbf{x}^{\diamond} + \mathbf{1}}$$
, $\delta_2 = \frac{\mathbf{1}}{\mathbf{x}^{\diamond} + \mathbf{1}}$

The nonlinear

$$\begin{cases} xy = \mu \\ y = x + 1 \end{cases}$$

$$\begin{array}{l} \text{is approximated} \\ \text{by the linear} \\ \text{system:} \end{array} \left\{ \begin{array}{l} \ln \, x \, + \, \ln \, y \, = \, \ln \, \, \mu \\ \\ \delta_1 \ln \, x \, - \, \ln \, y \, = \, \delta_1 \ln \, \delta_1 \, + \, \delta_1 \ln \, \delta_1 \end{array} \right.$$

that is,

$$\begin{cases} &z_x+\ z_y=\ln\ \mu\\ &\delta_1z_x-\ z_y=\delta_1\ln\ \delta_1+\ \delta_1\ln\ \delta_1 \end{cases}$$
 where
$$z_x=\ln\ x\,,\quad z_y=\ln\ y$$

In the Monomial Method, then, we solve

$$\begin{bmatrix} 1 & -1 \\ x^{\diamond}/_{x^{\diamond}+1} & -1 \end{bmatrix} \begin{bmatrix} z_{x} \\ z_{y} \end{bmatrix} = \begin{bmatrix} \ln \mu \\ C \end{bmatrix}$$

and update $x^{\diamond} \leftarrow exp(z_x) \ \& \ y^{\diamond} \leftarrow exp(z_y)$

while in Newton's Method, we solve

$$\begin{bmatrix} \mathbf{y}^{\diamond} & \mathbf{x}^{\diamond} \\ \mathbf{1} & -\mathbf{1} \end{bmatrix} \begin{bmatrix} \mathbf{\Delta}_{\mathbf{X}} \\ \mathbf{\Delta}_{\mathbf{y}} \end{bmatrix} = \begin{bmatrix} \mathbf{\mu}^{-} & \mathbf{x}^{\diamond} \mathbf{y}^{\diamond} \\ \mathbf{y}^{\diamond} - \mathbf{x}^{\diamond} - \mathbf{1} \end{bmatrix}$$

and update $x^{\diamond} \leftarrow x^{\diamond} + \Delta_x \& y^{\diamond} \leftarrow y^{\diamond} + \Delta_y$

Still another algorithm may be obtained by applying Newton's Method after making the logarithmic transformation:

$$\begin{cases} z_x + z_y = \ln \mu \\ e^{z_x} - e^{z_y} = -1 \end{cases}$$

which requires solving

$$\begin{bmatrix} \mathbf{1} & \mathbf{1} \\ \mathbf{ln} & \mathbf{x}^{\diamond} - \mathbf{ln} & \mathbf{y}^{\diamond} \end{bmatrix} \begin{bmatrix} d\mathbf{z}_{x} \\ d\mathbf{z}_{y} \end{bmatrix} = \begin{bmatrix} \mu - \mathbf{x}^{\diamond} \mathbf{y}^{\diamond} \\ \mathbf{y}^{\diamond} - \mathbf{x}^{\diamond} - \mathbf{1} \end{bmatrix}$$

and updating
$$z_{\mathbb{X}}^{\diamond} \leftarrow z_{\mathbb{X}}^{\diamond} + dz_{\mathbb{X}} \& z_{\mathbb{Y}}^{\diamond} \leftarrow z_{\mathbb{Y}}^{\diamond} + dz_{\mathbb{Y}}$$

Newton-Central

Newton's Method

$$\mu = 10^{-8}$$

stopping $|\mu-xy| + |y-x-1| \le 10^{-8}$

Starting point: (100, 10)

k	x ^k	\mathbf{y}^{k}	μ - x^ky^k	y ^k -x ^k -1
0 1 2 3 4 5 6 7 8 9	1E2 8.18182E0 3.85531E0 1.70635E0 6.59832E ⁻ 1 1.8769E ⁻ 1 2.5613E ⁻ 2 6.24066E ⁻ 4 3.9896E ⁻ 7 1.00002E ⁻ 8	1E1 9.18182E0 4.85531E0 2.70635E0 1.65983E0 1.18769E0 1.02561E0 1.00062E0 1E0	-1E3 -7.5124E1 -1.87187E1 -4.618E0 -1.09521E0 -2.22918E-1 -2.6269E-2 -6.24445E-4 -3.88961E-7	-9.1E1 -1.77636E-15 8.88178E-16 4.44089E-16 0E0 2.22045E-16 0E0 0E0 0E0 0E0



$$\mu = 10^{-8}$$

 $\begin{array}{l} \mu = 10^{-8} \\ \hline \textit{stopping} \\ \textit{criterion} \end{array} \left| \mu \text{-xy} \right| + \left| y \text{-x-1} \right| \leq \ 10^{-8} \end{array}$

Starting point: (100, 10)

k	x ^k	$\mathbf{y}^{\mathbf{k}}$	μ - x^ky^k	y ^k -x ^k -1
0	1E2	1E1	-1E3	-9.1E1
1	9.28919E ⁻⁵	1.07652E-4	1.8198E-23	-9.99985E-1
2	1.00076E ⁻⁸	9.99245E-1	8.27181E-24	-7.55405E-4
3	1E ⁻⁸	1E0	1.98523E-23	-2.88658E-15



An Infeasible Path-Following Algorithm using the Newton-Central Method

Equations to be approximately solved at each iteration

$$Ax - y = b$$

$$-Qx + A^{T}w + s = c$$

$$XSe = \mu e$$

$$WYe = \mu e$$

The logarithmic transformation is made, so that the complementarity equations are linearized, and the linear equations become nonlinear: $P(e^z) - Q(e^z) = 0$



An Infeasible Path-Following Algorithm using the Monomial Method

Equations to be approximately solved at each iteration

$$\begin{cases}
Ax - y = b \\
-Qx + A^{T}w + s = c \\
XSe = \mu e \\
WYe = \mu e
\end{cases}$$

The linear equations are approximated by monomial equations, and the logarithmic transformation is then made to linearize all the constraints.

- Start with any interior solution $(x^{\circ}, y^{\circ}, s^{\circ}, w^{\circ}) > 0$ set k=0, and choose 3 tolerances $\epsilon_1, \epsilon_2, \epsilon_3 > 0$
- $\begin{array}{ll} \text{Compute} & \mu^k = \sigma \; \frac{x^k s^k + y^k w^k}{n+m} \; , \qquad \quad \text{for} \; \; 0 < \sigma < 1 \\ & t_p^k = b \; + \; y^k \; \; Ax^k , \; \; \& \quad t_d^k = Qx^k \; + \; \mathbf{c} \; \; A^T \mathbf{w}^k \; \; \mathbf{s}^k \\ \end{array}$
- If $\mu^k \leq \epsilon_1, \frac{\left\|\mathbf{t}_p^k\right\|}{\|\mathbf{b}\|+1} \leq \epsilon_2, \; \& \; \frac{\left\|\mathbf{t}_d^k\right\|}{\left\|\mathbf{Q} x^k + \mathbf{c}\right\|+1} \leq \epsilon_3$

then stop & accept the current iterate as optimal.

- 3 Evaluate the weights
- 4 Compute coefficients & rhs of linear system
- 5 Solve linear system & return to step 1.

Properties of the sequence generated by this algorithm:

- exactly on the central trajectory
- strictly positive
- converges if bounded and the algorithm does not fail

Computational Experience



- Random subproblems with two variables, three constraints, and known solutions were randomly generated and used to build larger problems
- Separability was eliminated by performing a linear transformation.
 - For each problem size, ten random test problems were tested.
 - Initial solutions for Newton & Newton-Central algorithm are randomly generated but ON the central trajectory
- Initial solutions for Monomial algorithm are randomly generated but not on central trajectory

Number of	Separable Problems		Nonseparable Problems	
Subproblems	A	Q	A	Q
M=2 M=4 M=8 M=12	50% 25% 12.5% 8.33%	25% 12.5% 6.25% 4.17%	70% 60% 55% 53.33%	100% 100% 100% 100%
variablesconstraints	2M 3M		3M 5M	

Adjustment of factor σ^k

Standard Newton Algorithm:

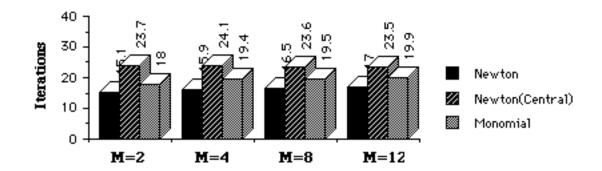
$$\sigma^{k+1} = \begin{cases} \min (0.95, 1.3\sigma^k) & \text{if } \frac{\mu^{k+1}}{\mu^k} < 1 \\ \max (0.2, 0.7\sigma^k) & \text{otherwise} \end{cases}$$

Newton-Central
$$\begin{split} \sigma^{k+1} &= \begin{cases} \min \ (0.95 \,,\, 1.3\sigma^k) \ \text{ if } \frac{error^{k+1}}{error^k} < 1 \\ \max \ (0.2 \,,\, 0.7\sigma^k) \ \text{ otherwise} \end{cases} \\ error^k &= \frac{t_p^k}{\|b\| + 1} + \frac{t_d^k}{\|Qx^k + c\| + 1} \end{split}$$
& Monomial Algorithms:

$$\mathbf{error}^{k} = \frac{\mathbf{t}_{p}^{k}}{\|\mathbf{b}\| + 1} + \frac{\mathbf{t}_{d}^{k}}{\|\mathbf{Q}\mathbf{x}^{k} + \mathbf{c}\| + 1}$$

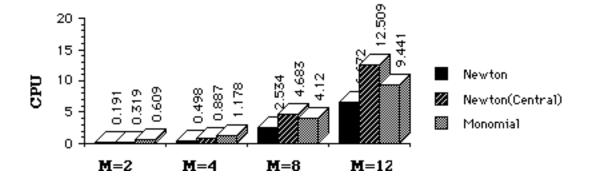
Separable Problems

Iterations vs ≠ subproblems



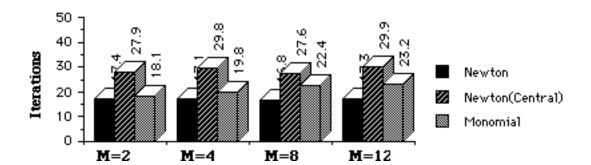
CPU vs ≠ subproblems

Separable Problems



Iterations vs. # subproblems

Nonseparable Problems



Nonseparable Problems

CPU vs # subproblems

