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# 理学院

081 系

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### A GLOBALLY CONVERGENT METHOD OF MOVING ASYMPTOTES WITH TRUST REGION TECHNIQUE

#### QIN NI\*

Nanjing University of Aeronautics and Astronautics, 210016 Nanjing, P.R. China

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The method of moving asymptotes is known to work well for certain problems arising in structural optimization. A globally convergent method of moving asymptotes with trust region technique is proposed in this paper. A convex separable subproblem is solved in each iteration. The choice of asymptotes is controlled by the trust region radius such that global convergence of the algorithm is obtained. In addition, preliminary numerical tests are given.

Keywords: Method of moving asymptotes; Trust region method; Structural optimization

#### 1 INTRODUCTION

We consider algorithms which combine moving asymptotes and trust region methods and which are designed for solving the following bound constrained optimization problem

$$\min \quad f(x) 
\text{s.t.} \quad x^l \le x \le x^u,$$
(1.1)

where  $x \in \mathbb{R}^n$ , the function f is assumed to be continuous in  $\Omega$  and twice continuously differentiable in the interior of  $\Omega$ ,  $\Omega = \{x \in \mathbb{R}^n : x^l \le x \le x^u\}$ ,  $x^l$  and  $x^u$  are finite fixed vectors. It is assumed that

$$b_m = \min_{1 \le i \le n} (x_i^u - x_i^l) \ge 0.$$
 (1.2)

The method of moving asymptotes (MMA) was firstly presented in [7], and frequently used for structural optimization. Afterwards this method was further studied and developed. Zillober combined the method with a line search, and obtained a kind of efficient global convergent sequential convex programming method [11,12]. For other extensions and developments see Refs. [2] and [8]. However, the properties of the moving asymptotes approximation is so far not thoroughly studied, the choice of the asymptotes is not very reasonable, and a global technique is complicated [9]. These may be a critical point of MMA. It is hoped that the famous trust region technique can improve MMA.

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<sup>\*</sup> Corresponding author. E-mail: niqfs@mail.nuaa.edu.cn

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The aim of this paper is to propose a globally convergent algorithm which combines the moving asymptotes approximation with the trust region technique. This algorithm is used to solve the bound constrained optimization problem. Through the convergence analysis of the algorithm the properties of moving asymptotes approximation and choice of asymptotes are analyzed and studied.

At first, we give some definitions and assumptions. The projected gradient  $\nabla_{\Omega} f$  of f is defined by

$$[\nabla_{\Omega} f(x)]_{i} = \begin{cases} \frac{\partial f}{\partial x_{i}}, & x_{i}^{l} < x_{i} < x_{i}^{u} \\ \min\left(0, \frac{\partial f}{\partial x_{i}}\right), & x_{i} = x_{i}^{l} \end{cases}$$

$$\max\left(0, \frac{\partial f}{\partial x_{i}}\right), \quad x_{i} = x_{i}^{u}$$

$$(1.3)$$

A point  $x \in \Omega$  is called to be a stationary point of problem (1.1) if  $\nabla_{\Omega} f(x) = 0$ . The projection operator P on  $\Omega$  is  $P(x) = (P_1[x_1], \dots, P_n[x_n])^T$ , where

$$P_i[x_i] = \begin{cases} x_i^l, & \text{if } x_i \le x_i^l \\ x_i^u, & \text{if } x_i \ge x_i^u \\ x_i, & \text{otherwise} \end{cases}$$
 (1.4)

We denote the set of all active bound constraints by I(x).

$$I(x) = \{i : x_i = x_i^u \text{ or } x_i = x_i^l, x \in \Omega\}.$$

This paper is organized as follows. We discuss the trust region subproblem in Section 2 and propose new algorithm in the subsequent section. The convergence of the algorithm is presented in Section 4 and numerical tests are given in Section 5.

#### 2 TRUST REGION SUBPROBLEM

The algorithm for solving (1.1) is of trust region type. At each iterate, a subproblem is defined by

$$\min_{d \in R^n} \quad m(x, d) = f(x) + \sum_{i=1}^n \phi_i(d_i) 
\text{s.t.} \quad d_i^l \le d_i \le d_i^u, \quad i = 1, \dots, n$$
(2.1)

where

$$d_i^u = \min(\Delta_i, x_i^u - x_i), \quad d_i^l = \max(-\Delta_i, x_i^l - x_i), \tag{2.2}$$

 $\Delta_i$  is trust region radius,

$$\phi_{i}(d_{i}) = \begin{cases} \frac{g_{i}d_{i}(u_{i} - x_{i})}{u_{i} - x_{i} - d_{i}} + \frac{\varepsilon_{i}d_{i}^{2}}{(u_{i} - x_{i} - d_{i})(x_{i} - l_{i} + d_{i})}, & i \in I_{+} \\ \frac{g_{i}d_{i}(x_{i} - l_{i})}{x_{i} - l_{i} + d_{i}} + \frac{\varepsilon_{i}d_{i}^{2}}{(u_{i} - x_{i} - d_{i})(x_{i} - l_{i} + d_{i})}, & i \in I_{-} \end{cases}$$
(2.3)

 $I_+ = \{i: g_i \ge 0\}, I_- = \{1, \dots, n\}/I_+, (g_1, \dots, g_n)^T = \nabla f(x). \ \varepsilon_i, l_i \ \text{and} \ u_i \ \text{are parameters},$  which satisfy

$$l_i < x_i < u_i, \quad \varepsilon_i > 0, \quad u_i - x_i - d_i > 0, \quad x_i - l_i + d_i > 0,$$
 (2.4)

for  $d_i \in [d_i^l, d_i^u]$ , i = 1, ..., n. Their detailed choice is discussed in Lemma 2.1 For convenience, some notations are introduced:

$$a_i = u_i - x_i, \quad b_i = x_i - l_i, \quad v_i = u_i - l_i, \quad i = 1, \dots, n.$$
 (2.5)

It follows from (2.4) that

$$a_i > 0, \quad b_i > 0, \quad v_i > 0, \quad v_i = a_i + b_i.$$
 (2.6)

It is easy to see that the subproblem (2.1) is separable and convex. It is equivalent to n independent one-dimensional bound constrained subproblems

$$\min_{\substack{d_i \\ \text{s.t.}}} \phi_i(d_i) \\
\text{s.t.} \quad d_i^l \le d_i \le d_i^u,$$
(2.7)

i = 1, ..., n. Because  $\phi_i(d_i)$  is a strictly convex function, there exists a unique optimal solution in (2.7). With some calculation, we have

$$\frac{\partial m(x,d)}{\partial d_{i}} = \phi'_{i}(d_{i}) = \begin{cases}
\frac{g_{i}a_{i}^{2}}{(a_{i}-d_{i})^{2}} + \frac{\varepsilon_{i}}{v_{i}} \left( \frac{a_{i}^{2}}{(a_{i}-d_{i})^{2}} - \frac{b_{i}^{2}}{(b_{i}+d_{i})^{2}} \right), & i \in I_{+} \\
\frac{g_{i}b_{i}^{2}}{(b_{i}+d_{i})^{2}} + \frac{\varepsilon_{i}}{v_{i}} \left( \frac{a_{i}^{2}}{(a_{i}-d_{i})^{2}} - \frac{b_{i}^{2}}{(b_{i}+d_{i})^{2}} \right), & i \in I_{-}
\end{cases} (2.8)$$

where we observe that

$$\frac{\varepsilon_i d_i^2}{(u_i-x_i-d_i)(x_i-l_i+d_i)} = \frac{\varepsilon_i d_i^2}{(a_i-d_i)(b_i+d_i)} = \frac{\varepsilon_i}{v_i} \left( \frac{a_i^2}{a_i-d_i} + \frac{b_i^2}{b_i+d_i} \right) - \varepsilon_i.$$

The function m(x, d) is a first-order approximation of f, i.e.

$$m(x, 0) = f(x), \quad \nabla_d m(x, 0) = (\phi'_1(0), \dots, \phi'_n(0))^T = (g_1, \dots, g_n)^T = \nabla f(x).$$

It is noted that an additional term in  $\phi_i(d_i)$  is similar to those in [8] and [11]. However, it is somewhat different. The minimal solution point of  $\phi_i(d_i)$  is bounded when  $\varepsilon_i$  approaches to  $0_+$ , which is discussed later. Other MMA approximations with usual additional terms do not possess this property.

Let  $\phi'_{i}(d_{i}) = 0$ , i.e.

$$0 = \frac{g_i a_i^2}{(a_i - d_i)^2} + \frac{\varepsilon_i}{v_i} \left( \frac{a_i^2}{(a_i - d_i)^2} - \frac{b_i^2}{(b_i + d_i)^2} \right) \quad \text{for } i \in I_+$$

which means

$$\left(\frac{a_i - d_i}{b_i + d_i}\right)^2 = \frac{a_i^2}{b_i^2} \left(1 + \frac{v_i g_i}{\varepsilon_i}\right).$$

By (2.4) and (2.6), we obtain

$$\frac{a_i - d_i}{b_i + d_i} = \frac{a_i \lambda_i}{b_i}$$

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where

$$\lambda_i = \left(1 + \frac{v_i g_i}{\varepsilon_i}\right)^{1/2}$$

and

$$d_i = \frac{a_i b_i (1 - \lambda_i)}{b_i + a_i \lambda_i} = \frac{a_i b_i (1 - \lambda_i^2)}{(1 + \lambda_i)(b_i + a_i \lambda_i)} = -\frac{a_i b_i v_i}{\varepsilon_i (1 + \lambda_i)(b_i + a_i \lambda_i)} g_i \quad \text{for } i \in I_+.$$

With the same deduction, we obtain the solution  $d'_i$  of  $\phi'_i(d_i) = 0$  as

$$d_i' = -\alpha_i' g_i \tag{2.9}$$

where

$$\alpha_{i}' = \begin{cases} \frac{a_{i}b_{i}v_{i}}{\varepsilon_{i}(\lambda_{i}+1)(b_{i}+\lambda_{i}a_{i})}, & i \in I_{+} \\ \frac{a_{i}b_{i}v_{i}}{\varepsilon_{i}(\lambda_{i}+1)(a_{i}+\lambda_{i}b_{i})}, & i \in I_{-} \end{cases} \quad \lambda_{i} = \begin{cases} \left(1+\frac{v_{i}g_{i}}{\varepsilon_{i}}\right)^{1/2}, & i \in I_{+} \\ \left(1-\frac{v_{i}g_{i}}{\varepsilon_{i}}\right)^{1/2}, & i \in I_{-} \end{cases}$$
(2.10)

Hence the solution of (2.7) is described by

$$d_i = -\alpha_i g_i \tag{2.11}$$

where

$$\alpha_{i} = \begin{cases} \alpha'_{i}, & \text{if } d'_{i} \in [d^{l}_{i}, d^{u}_{i}] \\ \frac{d^{l}_{i}}{-g_{i}}, & \text{if } d'_{i} < d^{l}_{i} \\ \frac{d^{u}_{i}}{-g_{i}}, & \text{if } d'_{i} > d^{u}_{i} \end{cases}$$
(2.12)

It follows from (2.9) and (2.10) that if  $g_i = 0$ , then  $d'_i = 0$ ; if  $g_i \neq 0$ , then

$$\lim_{\varepsilon_i \to 0_+} \varepsilon_i(\lambda_i + 1) = 0, \quad \lim_{\varepsilon_i \to 0_+} \varepsilon_i(\lambda_i + 1)\lambda_i = \begin{cases} v_i g_i, & i \in I_+ \\ -v_i g_i, & i \in I_- \end{cases}$$

and

$$\lim_{\varepsilon_i \to 0_+} d_i' = \begin{cases} -b_i, & i \in I_+ \\ a_i, & i \in I_- \end{cases}$$

which means the boundedness of the minimal solution of  $\phi_i(d_i)$ .

We define three sets by

$$J_1 = \{i : d'_i \in [d_i^l, d_i^u]\}, \quad J_2 = \{i : d'_i < d_i^l\}, \quad J_3 = \{i : d'_i > d_i^u\}. \tag{2.13}$$

In the following lemma, some conditions for parameters  $l_i$ ,  $u_i$  and  $\varepsilon_i$  are formulated, which guarantee the boundedness of  $\alpha'_i$ .

LEMMA 2.1 Assume that the parameters  $l_i$ ,  $u_i$  and  $\varepsilon_i$  satisfy the following conditions:

$$\begin{cases}
\max\{c_0(x_i^u - x_i^l) + \Delta_i, \ c_1(x_i^u - x_i^l)\} \le x_i - l_i \le c_2(x_i^u - x_i^l) \\
\max\{c_0(x_i^u - x_i^l) + \Delta_i, \ c_1(x_i^u - x_i^l)\} \le u_i - x_i \le c_2(x_i^u - x_i^l)
\end{cases}$$
(2.14)

$$\max\left(\varepsilon_{l}, \frac{|g_{i}|}{b_{\varepsilon}}\right) \leq \varepsilon_{i} \leq \varepsilon_{u} \tag{2.15}$$

i = 1, ..., n, where  $0 < c_0 < c_1 < 1 < c_2, 0 < \varepsilon_l < \varepsilon_u, b_{\varepsilon} > 0$ . Then,  $\alpha'_i$  is bounded, i.e.

$$\alpha_l \le \alpha_i' \le \alpha_u, \quad i = 1, \dots, n$$
 (2.16)

where

$$\alpha_l = \frac{c_1^2 b_m^2}{2\varepsilon_u (1 + 2c_2 b_\varepsilon b_M)} > 0, \quad \alpha_u = \frac{c_2^2 b_M^2}{2\varepsilon_l}, \quad b_M = \max_{1 \le i \le n} (x_i^u - x_i^l).$$

*Proof* From (2.10), (2.14) and (2.15), we obtain

$$1 \le \lambda_i^2 \le 1 + 2c_2b_{\varepsilon}b_M$$
  
$$c_1^2b_m^2v_i \le a_ib_iv_i \le c_2^2b_M^2v_i$$

Hence, from  $\lambda_i \geq 1$  and (2.6) it follows that

$$\varepsilon_i(\lambda_i + 1)(b_i + \lambda_i a_i) > \varepsilon_i(\lambda_i + 1)v_i > 2\varepsilon_i v_i$$

and

$$\varepsilon_i(\lambda_i+1)(b_i+\lambda_ia_i) \leq 2\varepsilon_i\lambda_i(b_i+\lambda_ia_i) \leq 2\varepsilon_i\lambda_i^2v_i \leq 2\varepsilon_u(1+2c_2b_\varepsilon b_M)v_i.$$

With the same deduction, we have

$$2\varepsilon_i v_i \leq \varepsilon_i (\lambda_i + 1)(a_i + \lambda_i b_i) \leq 2\varepsilon_u (1 + 2c_2 b_{\varepsilon} b_M) v_i$$
.

These imply that

$$\alpha_l \leq \alpha_i' \leq \alpha_u, \quad i = 1, \ldots, n.$$

 $\alpha_l > 0$  because of (1.2).

It is noted that the condition (2.14) is similar to that in [9], however the left side inequalities are different due to the trust region constraint. This means that for given  $\Delta_i$ , the parameters  $l_i$  and  $u_i$  have to satisfy

$$l_i < x_i - \Delta_i, \quad u_i > x_i + \Delta_i \tag{2.17}$$

which may be a reasonable control of  $l_i$  and  $u_i$ . In a practical implementation,  $\Delta_i$  in (2.14) can be replaced by  $\tilde{c}\Delta_i$ , ( $\tilde{c} \in (0, 1]$ ) when  $\Delta_i$  is relatively large. For the convenience in the proof, we only consider the case  $\tilde{c} = 1$ .

In order to obtain a main results about the subproblem, we estimate the difference between  $\phi_i(0)$  and  $\phi_i(d_i)$  in the following lemma.

LEMMA 2.2 Assume that  $d_i$  is the solution of (2.7) given in (2.11), then we have

$$\phi_{i}(0) - \phi_{i}(d_{i}) = \begin{cases} \alpha'_{i}\beta_{i}g_{i}^{2}, & i \in J_{1} \\ -d_{i}^{l}\beta_{i}g_{i}, & i \in J_{2} \\ -d_{i}^{u}\beta_{i}g_{i}, & i \in J_{3} \end{cases}$$
(2.18)

where

$$\beta_{i} = \begin{cases} \frac{a_{i}\lambda_{i}}{(a_{i} + \alpha'_{i}g_{i})(\lambda_{i} + 1)}, & i \in I_{+} \cap J_{1} \\ \frac{b_{i}\lambda_{i}}{(b_{i} - \alpha'_{i}g_{i})(\lambda_{i} + 1)}, & i \in I_{-} \cap J_{1} \\ \frac{a_{i}b_{i}}{(a_{i} - d_{i}^{l})(b_{i} + d_{i}^{l})(\lambda_{i} + 1)}, & i \in J_{2} \\ \frac{a_{i}b_{i}}{(a_{i} - d_{i}^{u})(b_{i} + d_{i}^{u})(\lambda_{i} + 1)}, & i \in J_{3} \end{cases}$$

$$(2.19)$$

*Proof* If  $i \in J_1$ , then it follows from (2.3) and (2.10) that

$$\phi_i(0) - \phi_i(d_i) = \phi_i(0) - \phi_i(-\alpha_i'g_i)$$
$$= \alpha_i'g_i^2\beta_i.$$

If  $i \in J_2$ , then  $g_i > 0$ ,  $i \in I_+$  and

$$\begin{aligned} \phi_{i}(0) - \phi_{i}(d_{i}) &= \phi_{i}(0) - \phi_{i}(d_{i}^{l}) \\ &= \frac{-d_{i}^{l}}{a_{i} - d_{i}^{l}} \left( g_{i} a_{i} + \frac{\varepsilon_{i} d_{i}^{l}}{b_{i} + d_{i}^{l}} \right) \\ &= \frac{-d_{i}^{l}}{(a_{i} - d_{i}^{l})(b_{i} + d_{i}^{l})} (g_{i} a_{i} b_{i} + d_{i}^{l}(g_{i} a_{i} + \varepsilon_{i})) \end{aligned}$$

The definition of  $J_2$  means that  $d_i^l > -\alpha_i' g_i$ . Taking into account the condition (2.6), we obtain

$$\phi_{i}(0) - \phi_{i}(d_{i}) \geq \frac{-d_{i}^{l}}{(a_{i} - d_{i}^{l})(b_{i} + d_{i}^{l})} (g_{i}a_{i}b_{i} - \alpha_{i}'g_{i}(g_{i}a_{i} + \varepsilon_{i}))$$

$$= \frac{-d_{i}^{l}g_{i}a_{i}b_{i}}{(a_{i} - d_{i}^{l})(b_{i} + d_{i}^{l})} \left(1 - \frac{v_{i}(a_{i}g_{i}/\varepsilon_{i} + 1)}{(\lambda_{i} + 1)(b_{i} + a_{i}\lambda_{i})}\right) \quad \text{cf. (2.10)}$$

$$= \frac{-d_{i}^{l}g_{i}a_{i}b_{i}}{(a_{i} - d_{i}^{l})(b_{i} + d_{i}^{l})} \frac{(\lambda_{i} + 1)(b_{i} + a_{i}\lambda_{i}) - (v_{i} + a_{i}(\lambda_{i}^{2} - 1))}{(\lambda_{i} + 1)(b_{i} + a_{i}\lambda_{i})} \quad \text{cf. (2.10)}$$

$$= \frac{-d_{i}^{l}g_{i}a_{i}b_{i}}{(a_{i} - d_{i}^{l})(b_{i} + d_{i}^{l})(\lambda_{i} + 1)} \frac{\lambda_{i}v_{i}}{b_{i} + a_{i}\lambda_{i}} \quad \text{cf. (2.6)}$$

$$\geq \frac{-d_{i}^{l}g_{i}a_{i}b_{i}}{(a_{i} - d_{i}^{l})(b_{i} + d_{i}^{l})(\lambda_{i} + 1)}$$

$$= \beta_{i}(-d_{i}^{l})g_{i}. \quad (2.20)$$

If  $i \in J_3$ , then  $-d_i^u > \alpha_i' g_i$ ,  $g_i < 0$ ,  $i \in I_-$  and

$$\begin{aligned} \phi_i(0) - \phi_i(d_i) &= \phi_i(0) - \phi_i(d_i^u) \\ &= \frac{d_i^u}{(a_i - d_i^u)(b_i + d_i^u)} ((-g_i)a_ib_i - d_i^u((-g_i)b_i + \varepsilon_i)) \end{aligned}$$

From the definition of  $J_3$  and condition (2.6), we obtain

$$\phi_{i}(0) - \phi_{i}(d_{i}) \geq \frac{d_{i}^{u}(-g_{i})}{(a_{i} - d_{i}^{u})(b_{i} + d_{i}^{u})} (a_{i}b_{i} - \alpha_{i}'((-g_{i})b_{i} + \varepsilon_{i}))$$

$$= \frac{d_{i}^{u}(-g_{i})a_{i}b_{i}}{(a_{i} - d_{i}^{u})(b_{i} + d_{i}^{u})} \frac{\lambda_{i}v_{i}}{(\lambda_{i} + 1)(a_{i} + \lambda_{i}b_{i})}$$

$$\geq \frac{d_{i}^{u}(-g_{i})a_{i}b_{i}}{(a_{i} - d_{i}^{u})(b_{i} + d_{i}^{u})(\lambda_{i} + 1)}$$

$$= \beta_{i}d_{i}^{u}(-g_{i}). \tag{2.21}$$

Thus, the lemma is proved.

Now we define

$$h(x) = P[x - D\nabla f(x)] - x \tag{2.22}$$

where  $D = \text{diag}(\alpha'_1, \dots, \alpha'_n), \alpha'_1, \dots, \alpha'_n$  are the same as in (2.10), then a main result is described in the following theorem.

THEOREM 2.3 Assume that the conditions (2.14) and (2.15) are satisfied, then we have

$$f(x) - m(x, d) \ge \beta \min\left(1, \frac{\Delta m}{b_M}\right) \|h(x)\|^2, \tag{2.23}$$

where  $\beta = \min_{1 \le i \le n} (\beta_i / \alpha_i') > 0, \Delta_m = \min_{1 \le i \le n} \Delta_i$ .

*Proof* If  $i \in J_1$ , then

$$h_i(x) = P_i[x_i - \alpha_i'g_i] - x_i = -\alpha_i'g_i.$$

From (2.18), we obtain

$$\phi_i(0) - \phi_i(d_i) = \frac{\beta_i}{\alpha_i'} h_i^2(x). \tag{2.24}$$

If  $i \in J_2$ , then we have from (2.13) that  $d_i^l > -\alpha_i' g_i$ ,  $g_i > 0$  and  $x_i - \alpha_i' g_i < x_i^u$  because of  $\alpha' > 0$  and  $d_i^l \le 0$ . Consider three cases in  $J_2$ .

(1) If  $x_i = x_i^l$ , then

$$h_i(x) = P_i[x_i - \alpha_i'g_i] - x_i = 0.$$

From (2.3) and  $d_i^l = \max\{-\Delta_i, x_i^l - x_i\} = 0$ , it follows that

$$\phi_i(0) - \phi_i(d_i) = \phi_i(0) - \phi_i(d_i^l) = 0.$$
(2.25)

(2) If  $x_i > x_i^l$ ,  $x_i - x_i^l \le \Delta_i$ , then  $d_i^l = x_i^l - x_i$ ,  $x_i - \alpha_i' g_i < x_i + d_i^l = x_i^l$ , and  $h_i(x) = P_i[x_i - \alpha_i' g_i] - x_i = x_i^l - x_i = d_i^l.$ 

From (2.20), we have that

$$\phi_i(0) - \phi_i(d_i) = \frac{\beta_i}{\alpha_i'} |d_i^l| |\alpha_i' g_i| \ge \frac{\beta_i}{\alpha_i'} h_i^2(x).$$
 (2.26)

(3) If  $x_i > x_i^l$ ,  $x_i - x_i^l > \Delta_i$ , then  $d_i^l = -\Delta_i$ . From (2.22), we obtain

$$|h_i(x)| = |P_i[x_i - \alpha_i'g_i] - x_i| \le \min(x_i - x_i^l, |\alpha_i'g_i|).$$

From (2.20), we obtain

$$\phi_{i}(0) - \phi_{i}(d_{i}) \ge -d_{i}^{l}g_{i}\beta_{i} \ge \frac{\Delta_{i}\beta_{i}}{\alpha_{i}'}(\alpha_{i}'g_{i})\frac{x_{i} - x_{i}^{l}}{x_{i}^{u} - x_{i}^{l}} \ge \frac{\beta_{i}}{\alpha_{i}}\frac{\Delta_{i}}{x_{i}^{u} - x_{i}^{l}}h_{i}^{2}(x). \tag{2.27}$$

If  $i \in J_3$ , then we have that  $g_i < 0$  and  $x_i - \alpha'_i g_i > x_i^l$  because of  $\alpha' > 0$  and  $d_i^u \ge 0$ . With a similar deduction, we obtain

$$\phi_{i}(0) - \phi_{i}(d_{i}) = \frac{\beta_{i}}{\alpha'_{i}} h_{i}^{2}(x), \quad \text{if } x_{i} = x_{i}^{u}, 
\phi_{i}(0) - \phi_{i}(d_{i}) \ge \frac{\beta_{i}}{\alpha'_{i}} h_{i}^{2}(x), \quad \text{if } x_{i} > x_{i}^{u}, x_{i}^{u} - x_{i} \le \Delta_{i}.$$
(2.28)

If  $x_i < x_i^u$ ,  $x_i^u - x_i > \Delta_i$ , then  $d_i^u = \Delta_i$ , and

$$\phi_i(0) - \phi_i(d_i) \ge \frac{\beta_i}{\alpha_i'} \frac{\Delta_i}{x_i^u - x_i^l} h_i^2(x).$$
 (2.29)

The inequalities (2.24)–(2.29) together imply that (2.23) is valid. In addition, Lemma 2.1 and (2.19) imply that  $\beta > 0$ .

In addition, we have the following statement.

LEMMA 2.4 Let  $x \in \Omega$ , D is defined by (2.22),  $l_i$ ,  $u_i$ ,  $\varepsilon_i$  satisfy (2.14) and (2.15). Then x is a stationary point for (1.1) if and only if

$$h(x) = P[x - tD\nabla f(x)] - x = 0$$

for all  $t \geq 0$ .

*Proof* From Lemma 2.1, we obtain that *D* is diagonal and positive definite. Hence, this lemma results immediately from Proposition 1.35 of [1].

#### 3 ALGORITHM

We are now able to outline the new algorithm, which combines the moving asymptotes approximation with trust region technique.

#### ALGORITHM 3.1

Step 0 Choose  $x_0 \in \Omega$ , k = 0. Choose the constants  $c_0$ ,  $c_1$ ,  $c_2$ ,  $\varepsilon_l$ ,  $\varepsilon_u$ ,  $b_{\varepsilon}$ ,  $\eta_1$ ,  $\eta_2$ ,  $r_1$ ,  $r_2$  and  $r_3$  such that  $0 < c_0 < c_1 < 1 < c_2, 0 < \varepsilon_l < \varepsilon_u, b_{\varepsilon} > 0, 0 \le \eta_1 < \eta_2 < 1, 0 < r_1 \le \eta_2 < 1$  $r_2 < 1 < r_3$ , and define the initial trust region radius  $\Delta_i^0 > 0$ , i = 1, ..., n.

Step 1 Compute  $f(x^k)$ ,  $g_k$ , and define a subproblem (2.1). Let  $d^k$  be its solution (see (2.7)). If  $d^k = 0$ , then stop.

Step 2 Compute

$$\rho_k = \frac{f(x^k + d^k) - f(x^k)}{m(x^k, d^k) - f(x^k)}$$
(3.1)

If

$$\rho_k \ge \eta_1,\tag{3.2}$$

then  $x^{k+l} = x^k + d^k$ , otherwise  $x^{k+1} = x^k$ .

Step 3 Update  $\Delta_k$ .

$$\Delta_i^{k+1} \in \begin{cases} [r_2 \Delta_i^k, \Delta_i^k], & \text{if } \rho_k < \eta_2 \\ [\Delta_i^k, r_3 \Delta_i^k], & \text{otherwise} \end{cases}$$
 (3.3)

 $i=1,\ldots,n.$  Step 4 Update  $l_i^{k+1}$ ,  $u_i^{k+1}$  and  $\varepsilon_i^{k+1}$  such that (2.14) and (2.15) are satisfied. Step 5 k = k + 1, go to Step 1.

#### Remarks

- (1) An iteration in Algorithm 3.1 is called successful if the test (3.2) is satisfied, and unsuccessful otherwise.
- (2) If the solution of (2.7), d (see (2.9) and (2.10)) is nonzero, then the test (3.2) is easily satisfied, if the trust region radius is small enough. If d=0, then a stationary point is reached, which is described in the following lemma.

LEMMA 3.1 Let d be a solution of (2.7). Then d = 0 if and only if  $\nabla_{\Omega} f(x) = 0$ .

*Proof* From (2.9) and  $\alpha'_i \geq \alpha_l > 0$  in Lemma 2.1, it follows that

$$d_i = 0 \iff g_i = 0$$
, for all  $i \in J_1$ .

If  $i \in J_2$ , then from (2.11) to (2.13) we have  $d_i = d_i^l$ ,  $g_i > 0$ ,  $\min(0, g_i) = 0$ , because  $\alpha'_i > 0$  and  $d_i^l \le 0$  (see (2.2)). Hence, we obtain

$$d_i = 0 \iff d_i^l = 0 \iff x_i^l = x_i \text{ (because } \Delta_i > 0),$$

i.e.

$$d_i = 0 \Longleftrightarrow x_i^l = x_i$$
, and  $\min(0, g_i) = 0$  for all  $i \in J_2 \Longleftrightarrow (\nabla_{\Omega} f(x))_i = 0$ .

With a similar deduction, we obtain

$$d_i = 0 \Longleftrightarrow x_i^u = x_i$$
, and  $\max(0, g_i) = 0$  for all  $i \in J_3 \Longleftrightarrow (\nabla_{\Omega} f(x))_i = 0$ .

This lemma means that if x is not a stationary point, then d in (2.9) is nonzero.

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#### 4 GLOBAL CONVERGENCE PROPERTY OF THE ALGORITHM

In this section we discuss the global convergence of Algorithm 3.1. We first define

 $S = \{k: \text{ the } k \text{th iteration is successful in Algorithm 3.1} \}$ 

and the curvature of the differentiable function f along the step d ( $d \neq 0$ ) and based at the point  $x \in \Omega$  by

$$w(f, x, d) = \frac{1}{\|d\|^2} [f(x+d) - f(x) - \nabla f(x)^T d]. \tag{4.1}$$

In a similar way we define

$$\tilde{w}(m, x, d) = \frac{1}{\|d\|^2} [m(x, d) - m(x) - \nabla_d m(x, 0)^T d]$$
(4.2)

where  $d \neq 0$ . It is noted that the function f is assumed to be continuous in  $\Omega$  and twice continuously differentiable in the interior of  $\Omega$  in the following lemmas and theorems. Now we have the statement for w(f, x, d) and  $\tilde{w}(m, x^k, d^k)$ .

LEMMA 4.1 There exist constants  $c_3 > 0$  and  $c_4 > 0$  such that

$$|w(f,x,d)| \le c_3,\tag{4.3}$$

$$\|\nabla f(x)\|_{\infty} \le c_4,\tag{4.4}$$

where  $d \in \mathbb{R}^n$ ,  $d \neq 0$ , x,  $x + d \in \Omega$ .

The proof of this lemma is easy and is omitted.

LEMMA 4.2 There exists a constant  $c_5 > 0$  such that

$$0 < \tilde{w}(m, x^k, d^k) \le c_5 \tag{4.5}$$

where  $d^k \neq 0$  is the solution of (2.7) at  $x^k$ ,

$$c_5 = \frac{c_4 c_0 b_m + \varepsilon_u}{c_0^2 b_m^2}. (4.6)$$

*Proof* From (4.1) and (2.1) it follows that

$$||d^{k}||^{2} \tilde{w}(m, x^{k}, d^{k}) = (m(x^{k}, d^{k}) - m(x^{k}, 0) - \nabla_{d} m(x^{k}, 0)^{T} d^{k})$$

$$= \sum_{i=1}^{n} \phi(d_{i}^{k}) - \sum_{i=1}^{n} \phi'(0) d_{i}^{k}$$

$$= \sum_{i=1}^{n} (\phi(d_{i}^{k}) - g_{i} d_{i}^{k})$$

$$= \frac{1}{2} \sum_{i=1}^{n} \alpha_{ki} (d_{i}^{k})^{2}$$
(4.7)

where  $\alpha_{ki}$  is obtained after simple calculation

$$\alpha_{ki} = \begin{cases} \frac{2g_i}{a_i^k - d_i^k} + \frac{2\varepsilon_i}{(a_i^k - d_i^k)(b_i^k + d_i^k)}, & i \in I_+ \\ \frac{-2g_i}{b_i^k + d_i^k} + \frac{2\varepsilon_i}{(a_i^k - d_i^k)(b_i^k + d_i^k)}, & i \in I_- \end{cases}.$$

From (2.14), (2.15) and (4.4), it follows that

$$a_i^k - d_i^k \ge c_0(x_i^u - x_i^l) \ge c_0 b_m, \quad b_i^k + d_i^k \ge c_0 b_m,$$

and

$$0 < \alpha_{ki} \le 2c_5.$$

If we define

$$\Delta_{km} = \min_{1 \le i \le n} (\Delta_i^k), \quad \Delta_{kM} = \max_{1 \le i \le n} (\Delta_i^k), \quad c_6 = \left(\frac{\max_{1 \le i \le n} (\Delta_i^0)}{\min_{1 \le i \le n} (\Delta_i^0)}\right)^2$$

then it is easy to see from Algorithm 3.1 that

$$\Delta_{kM}^2 \le c_6 \Delta_{km}^2. \tag{4.8}$$

The following statement is somewhat different from general trust region methods, but the proof is similar.

LEMMA 4.3 Consider a sequence  $\{x^k\}$  generated by Algorithm 3.1, and assume that there exists a constant  $\varepsilon > 0$  such that

$$||h(x^k)|| \ge \varepsilon \tag{4.9}$$

for all k, where  $h(x^k)$  is defined by (2.22). Then there is a constant  $c_7 > 0$  such that

$$\Delta_{km} \ge c_7 \tag{4.10}$$

*Proof* From (4.8), lemmas 4.1 and 4.2, it follows that

$$|f(x^{k} + d^{k}) - m(x^{k}, d^{k})| \leq \frac{1}{2} ||d^{k}||^{2} |w(f, x^{k}, d^{k}) - \tilde{w}(m, x^{k}, d^{k})|$$

$$\leq \frac{1}{2} ||d^{k}||^{2} (|w(f, x^{k}, d^{k})| + |\tilde{w}(m, x^{k}, d^{k})|)$$

$$\leq \frac{1}{2} ||d^{k}||^{2} (c_{3} + c_{5}) \leq \frac{1}{2} (c_{3} + c_{5}) \Delta_{kM}^{2}$$

$$\leq \frac{1}{2} (c_{3} + c_{5}) c_{6} \Delta_{km}^{2}$$

$$(4.11)$$

We assume, without loss of generality, that

$$\varepsilon < \min \left\{ 1, b_M \left( \frac{(c_3 + c_5)c_6}{2(1 - \eta_2)\beta} \right)^{1/2} \right\},$$
 (4.12)

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where  $\beta$  refers to Theorem 2.3,  $\eta_2$  refers to Step 3 in Algorithm 3.1. In order to derive a contradiction, we assume that there exists a k such that

$$\frac{1}{2}(c_3 + c_5)c_6b_M\Delta_{km} \le r_1\beta(1 - \eta_2)\varepsilon^2 \tag{4.13}$$

where  $r_1$  refers to Step 0 in Algorithm 3.1 and r is defined as the first iteration number such that (4.13) holds.

With Step 3 in Algorithm 3.1 we obtain

$$c_{5}c_{6}b_{M}\Delta_{r-1,m} \leq (c_{3}+c_{5})c_{6}b_{M}\Delta_{r-1,m}$$

$$\leq \frac{(c_{3}+c_{5})c_{6}b_{M}\Delta_{rm}}{r_{1}}$$

$$\leq 2(1-\eta_{2})\beta\varepsilon^{2}.$$
(4.14)

From Theorem 2.3, it follows that

$$f(x_{r-1}) - m(x_{r-1} + d_{r-1}) \ge \beta \min\left(1, \frac{\Delta_{r-1,m}}{b_M}\right) \|h(x_{r-1})\|^2.$$

Without loss of generality, assume that

$$\frac{\Delta_{km}}{b_M} \le 1, \quad k = 1, 2, \dots,$$

Then we have

$$f(x_{r-1}) - m(x_{r-1} + d_{r-1}) \ge \frac{\beta \Delta_{r-1,m} \varepsilon^2}{b_M}.$$
 (4.15)

(3.1), (4.11), (4.14) and (4.15) together means that

$$|\rho_{r-1} - 1| = \frac{|f(x_{r-1} + d_{r-1}) - m(x_{r-1} + d_{r-1})|}{|f(x_{r-1}) - m(x_{r-1} + d_{r-1})|} \le \frac{(c_3 + c_5)c_6b_M\Delta_{r-1,m}}{2\beta\varepsilon^2} < 1 - \eta_2.$$
(4.16)

This implies that  $\rho_{r-1} \geq \eta_2$ , and therefore  $\Delta_{rm} \geq \Delta_{r-1,m}$ . Hence, we obtain that

$$\frac{1}{2}(c_3 + c_5)c_6b_M\Delta_{r-1,m} \le \frac{1}{2}(c_3 + c_5)c_6b_M\Delta_{rm} \le r_1\beta(1 - \eta_2)\varepsilon^2 \tag{4.17}$$

which contradicts the assumption that r was the first index satisfying (4.13). Therefore, (4.13) never holds, and

$$\frac{1}{2}(c_3 + c_5)c_6b_M\Delta_{km} > r_1\beta(1 - \eta_2)\varepsilon^2$$

for all k. Hence we obtain

$$\Delta_{km} \geq c_7$$

for all k, where

$$c_7 = \frac{2r_1\beta(1-\eta_2)\varepsilon^2}{(c_3+c_5)c_6b_M}.$$