

**METHOD OF « CLEFT-OVERSTEP » BY PERPENDICULAR  
DIRECTION FOR SOLVING THE UNCONSTRAINED NONLINEAR  
OPTIMIZATION PROBLEM**

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INTRODUCTION

We shall be concerned with the following unconstrained nonlinear optimization problems :

$$\text{minimize } J(u), \text{ subject to } u \in E^n,$$

where  $J(u)$  is a nonlinear function and  $E^n$  is the  $n$ -dimensional Euclidean space.

In [1], an algorithm of « cleft-overstep » called the algorithm of quasi-bisector is proposed for solving this problem.

Based on the method of « cleft-overstep » we present in this paper a new method called the algorithm of « cleft-overstep » by perpendicular direction. Some examples are given in § 5.

I. DESCRIPTION OF THE ALGORITHM

We shall denote by  $\| \cdot \|$  the Euclidean norm and by  $\langle \dots \rangle$  the inner product in  $E^n$ . Suppose that  $J(u)$  is continuously differentiable and that the gradient mapping  $J'(u)$  satisfies the Lipschitz condition with a constant  $L$ . Let  $s^k \in E^n$  denote the vector showing the changed direction of the function  $J(u)$  on step  $k+1$  ( $k=0, 1, 2, \dots$ ). Taking  $u^0 \in E^n$  as the starting point, we construct a sequence of points  $\{u^k\}$  by the method of « cleft-overstep » as follows :

$$u^k = u^{k-1} + \alpha_k S^{k-1}, \quad k = 1, 2, 3, \dots \quad (1)$$

$$S^0 = -J'(u^0), \quad S^k = -J'(u^k) + \beta_k S^{k-1}, \quad k = 1, 2, \dots \quad (2)$$

$$\beta_k = \begin{cases} 0, & \text{if } k \in I_1 \\ \frac{\langle y, \mathcal{J}'(u^k) \rangle}{\langle y, S^{k-1} \rangle}, & \text{if } k \in I_2, y = S^{k-1} + \mathcal{J}'(u^k) \end{cases} \quad (3)$$

Where  $I_1$  is the set of indices  $k=0, n, 2n, \dots$  and of satisfying those indices  $k$

$$\text{either } \frac{\|S^{k-1}\|}{\|\mathcal{J}'(u^k)\|} \leq \varepsilon_1 \quad (4)$$

$$\text{or } |\cos \varphi_{k-1}| = \frac{\langle \mathcal{J}'(u^k), S^{k-1} \rangle}{\|\mathcal{J}'(u^k)\| \cdot \|S^{k-1}\|} > \varepsilon_2, 1 > \varepsilon_1 > \varepsilon_2 > 0;$$

$$I_2 = \{0, 1, 2, \dots\} \setminus I_1;$$

$\alpha_k$ , ( $k = 1, 2, \dots$ ) is the step length, satisfying the following « cleft-overstep » condition :

$$J(u^{k-1} + \alpha_k S^{k-1}) \leq J(u^{k-1} + \varepsilon S^{k-1}), 0 < \varepsilon < 1$$

$$\left. \frac{\partial J(u^{k-1} + \alpha S^{k-1})}{\partial \alpha} \right|_{\alpha = \alpha_k} > 0. \quad (5)$$

## 2. THE BASIC LEMMAS

LEMMA 1. Suppose that  $J'(u^k) \neq 0$  for all  $k$ . If  $S^k$  is a moving direction constructed using (1) - (5), then there exist  $A_1 > 0$  and  $A_2 > A_1$  such that

$$A_1 \|\mathcal{J}'(u^k)\|^2 \leq \|S^k\| \leq A_2 \|\mathcal{J}'(u^k)\|^2. \quad (6)$$

LEMMA 2. Under the conditions as of Lemma 1,  $S^k$  is always a decreasing direction of  $J(u)$ , and the following inequality is satisfied for some  $A_3 > 0$

$$-\langle \mathcal{J}'(u^k), S^k \rangle \geq A_3 \|\mathcal{J}'(u^k)\|^2 \geq 0. \quad (7)$$

LEMMA 3. If  $J(u)$  is continuously differentiable and bounded from below and if the set  $M(u^0) = \{u \mid J(u) \leq J(u^0)\}$  is bounded then the « cleft-overstep » condition (5) is always satisfied in  $M(u^0)$ .

LEMMA 4. If  $J(u)$  is continuously differentiable and bounded from below then there exists  $\alpha > 0$  such that :

$$\frac{\partial \mathcal{J}(u^k + \alpha S^{k-1})}{\partial \alpha} \geq 0,$$

$$\mathcal{J}(u^{k-1} + \alpha S^{k-1}) \leq \mathcal{J}(u^{k-1} + \varepsilon S^{k-1}), \quad (8)$$

where  $\varepsilon$  is the positive number chosen by (5).

### 3. CONVERGENCE AND THE RATE OF CONVERGENCE

THEOREM 1. Suppose that  $J(u)$  is continuously differentiable and is bounded from below, and that  $J(u)$  satisfies the Lipschitz condition with a constant  $L$ , then for every starting point  $u^0 \in E_n$ , the sequence  $\{u^k\}$ , constructed by the above rule (1) — (5) has cluster points which are critical points of  $J(u)$ .

Furthermore, if  $J(u)$  is a convex function and if the set  $M(u^0) = \{u | J(u) \leq J(u^0)\}$  is bounded, then  $\{u^k\}$  is a minimizing sequence for  $J(u)$ . In the case when the minimum point is unique the sequence  $\{u^k\}$  converges to this point.

THEOREM 2. Suppose that  $J(u)$  is a convex function, continuously differentiable in  $E^n$  and that  $J(u)$  satisfies the Lipschitz condition with a constant  $L$ . If  $\{u^k\}$  is the sequence constructed by the rule (1) — (5), then

$$0 < \mathcal{J}(u^k) - \mathcal{J}^* \leq \frac{D^2}{A_4} \cdot \frac{1}{k}, \quad A_4 = \frac{a \varepsilon A_3}{a + 1}, \quad a > 0 \quad (9)$$

where  $D = \text{Sup} \|u - v\|$  is the diameter of the set  $M(u^0)$ , and  
 $J^* = \inf_{u, v \in M(u^0)}$   
 $J^* = \inf J(u) = J(u^*)$ .

Moreover, if  $J(u)$  is a strongly convex function in  $E^n$  then

$$0 < \mathcal{J}(u^k) - \mathcal{J}^* \leq (\mathcal{J}(u^0) - \mathcal{J}^*) q^k \quad (10)$$

$$\|u^k - u^*\|^2 \leq \frac{2}{\mathcal{X}} (\mathcal{J}(u^0) - \mathcal{J}^*) q^k, \quad (11)$$

$$q = 1 - A_4 \mu; \quad 0 < q < 1; \quad \mathcal{X}, \mu = \text{constant} > 0$$

#### 4. PROOF OF THE LEMMAS AND THEOREMS

##### 4.1 Proof of Lemma 1.

By (1) — (5), if  $k \in I_1$  or  $S^{k-1} \equiv 0$  then  $S^k \equiv -J'(u^k)$  and, hence,

$$\|S^k\|^2 = \|J'(u^k)\|^2, \quad A_1 = A_2 = 1.$$

The inequality; (6) becomes equality.

If  $k \in I_2$  and  $S^{k-1} \neq 0$  then we have:

$$\begin{aligned} \beta_k &= \frac{\langle y, \mathcal{J}'(u^k) \rangle}{\langle y, S^{k-1} \rangle} = \frac{\langle \mathcal{J}'(u^k) + S^{k-1}, \mathcal{J}'(u^k) \rangle}{\langle \mathcal{J}'(u^k) + S^{k-1}, S^{k-1} \rangle} = \\ &= \frac{\|\mathcal{J}'(u^k)\|^2 + \langle \mathcal{J}'(u^k), S^{k-1} \rangle}{\|S^{k-1}\|^2 + \langle \mathcal{J}'(u^k), S^{k-1} \rangle} = \\ &= \frac{\|\mathcal{J}'(u^k)\| / \|S^{k-1}\| + \langle \mathcal{J}'(u^k), S^{k-1} \rangle / (\|\mathcal{J}'(u^k)\| \cdot \|S^{k-1}\|)}{\|S^{k-1}\| / \|\mathcal{J}'(u^k)\| + \langle \mathcal{J}'(u^k), S^{k-1} \rangle / (\|\mathcal{J}'(u^k)\| \cdot \|S^{k-1}\|)} \\ &= \frac{1/\gamma + \cos\varphi_{k-1}}{\gamma + \cos\varphi_{k-1}}, \quad \text{where } \gamma = \frac{\|S^{k-1}\|}{\|\mathcal{J}'(u^k)\|} \end{aligned}$$

At the same time

$$\begin{aligned} \|S^k\|^2 &= \|\mathcal{J}'(u^k) + \beta_k S^{k-1}\|^2 = \|\mathcal{J}'(u^k)\|^2 + \beta_k^2 \|S^{k-1}\|^2 - 2\beta_k \langle \mathcal{J}'(u^k), \\ &S^{k-1} \rangle = \|\mathcal{J}'(u^k)\|^2 \left[ 1 + \beta_k^2 \frac{\|S^{k-1}\|^2}{\|\mathcal{J}'(u^k)\|^2} - 2\beta_k \frac{\langle \mathcal{J}'(u^k), S^{k-1} \rangle}{\|\mathcal{J}'(u^k)\|^2} \right] = \\ &= \|\mathcal{J}'(u^k)\|^2 \left[ 1 + \beta_k^2 \gamma^2 - 2\beta_k \gamma \cos\varphi_{k-1} \right]. \end{aligned}$$

We consider the expression:

$$A = 1 + \beta_k^2 \gamma^2 - 2\beta_k \gamma \cos\varphi_{k-1}.$$

Denoting  $x = \beta_k \gamma$  we have

$$0 < x = \frac{1/\gamma + \cos\varphi_{k-1}}{\gamma + \cos\varphi_{k-1}} \cdot \gamma = \frac{1/\gamma + \cos\varphi_{k-1}}{1 + (\cos\varphi_{k-1})/\gamma} < \frac{1}{\varepsilon_1} + \varepsilon_2.$$

(Taking into account the « cleft-overstep » condition (5), at the point  $u^k$  the direction  $S^{k-1}$  is an increasing direction of the objective function  $J(u)$ . Therefore  $\cos\varphi_{k-1} > 0$ ).

It follows that

$$A = 1 + x^2 - 2x \cos \varphi_{k-1} \leq 1 + x^2 \leq 1 + (1/\varepsilon_1 + \varepsilon_2)^2 = A_2$$

On the other hand,  $1 + x - 2x \cos \varphi_{k-1}$ , as a function of  $x$ , reaches its minimum value at a point such that

$$A'_x = 0 \Leftrightarrow 2x - 2 \cos \varphi_{k-1} = 0 \Rightarrow x^* = \cos \varphi_{k-1}$$

Therefore

$$A > 1 + \cos^2 \varphi_{k-1} - 2 \cos^2 \varphi_{k-1} = 1 - \cos^2 \varphi_{k-1} \geq 1 - \varepsilon_2^2 = A_1$$

We have thus proved that

$$(1 - \varepsilon_2^2) \|\mathcal{J}'(u^k)\|^2 < \|S^k\|^2 < [1 + (1/\varepsilon_1 + \varepsilon_2)^2] \cdot \|\mathcal{J}'(u^k)\|^2,$$

where

$$A_2 = 1 + (1/\varepsilon_1 + \varepsilon_2)^2 > A_1 = 1 - \varepsilon_2^2 > 0.$$

The proof of Lemma 1 is complete:

#### 4.2 Proof of Lemma 2.

For the sake of simplicity we denote  $a = J'(u^k)$ ,  $b = S^{k-1}$ . If  $k \in I_1$  or  $S^{k-1} \equiv 0$  then  $S^k = -J'(u^k)$ . Lemma 2 is trivial

In the other cases when  $k \in I_2$  and  $S^{k-1} \neq 0$  we have

$$\begin{aligned} -\langle \mathcal{J}'(u^k), S^k \rangle &= \langle -\mathcal{J}'(u^k), -\mathcal{J}'(u^k) + \beta_k S^{k-1} \rangle = \\ &= \langle -a, -a + \frac{\langle a, a+b \rangle}{\langle b, a+b \rangle} \cdot b \rangle = \|a\|^2 - \frac{\|a\|^2 + \langle a, b \rangle}{\|b\|^2 + \langle a, b \rangle} \cdot \langle a, b \rangle = \\ &= \frac{\|a\|^2 \|b\|^2 + \langle a, b \rangle \|a\|^2 - \|a\|^2 \langle a, b \rangle - \langle a, b \rangle^2}{\|b\|^2 + \langle a, b \rangle} = \\ &= \frac{\|a\|^2 \cdot \|b\|^2 - \langle a, b \rangle^2}{\|b\|^2 + \langle a, b \rangle} = \frac{1 - (\langle a, b \rangle / (\|a\| \cdot \|b\|))}{1 + \langle a, b \rangle / \|b\|^2} \cdot \|a\|^2 = \\ &= \frac{1 - \cos^2 \varphi_{k-1}}{1 + \frac{\langle a, b \rangle \|a\|}{\|a\| \cdot \|b\|}} \cdot \|a\|^2 = \frac{1 - \cos^2 \varphi_{k-1}}{1 + \frac{\cos^2 \varphi_{k-1}}{\gamma}} \|a\|^2 \geq \\ &\geq \frac{1 - \varepsilon_2^2}{1 + \varepsilon_2/\varepsilon_1} \|a\|^2; \end{aligned}$$

Hence

$$-\langle \mathcal{J}'(u^k), S^k \rangle \geq A_3 \|\mathcal{J}'(u^k)\| > 0,$$

where

$$A_3 = \frac{1 - \varepsilon_2^2}{1 + \varepsilon_1/\varepsilon_2}.$$

This result shows that  $S^k$  form an obtuse angle with  $\mathcal{J}'(u^k)$  because their scalar product is a negative number. Therefore  $S^k$  is a decreasing direction for  $J(u)$ . This completes the proof of Lemma 2. The proofs of Lemma 3 and Lemma 4 are similar to those used in [1] and will therefore be omitted.

### 4.3 Proof of Theorem 1

First we rewrite (5) as

$$\mathcal{J}(u^{k-1}) - \mathcal{J}(u^{k-1} + \alpha_k S^{k-1}) \geq \mathcal{J}(u^{k-1}) - \mathcal{J}(u^{k-1} + \varepsilon S^{k-1}),$$

where,  $\varepsilon$  is chosen according to the condition (5) so that

$$0 < \varepsilon \leq \frac{2A_3}{A_2 L(a+1)},$$

Using the same way as in the proof of Theorem 1 in [1] we have

$$\begin{aligned} \mathcal{J}(u^k) - \mathcal{J}(u^k + \varepsilon S^k) &\geq -\varepsilon \langle S^k, \mathcal{J}'(u^k) \rangle \left[ 1 + \frac{\varepsilon L}{2} \cdot \frac{\|S^k\|^2}{\langle S^k, \mathcal{J}'(u^k) \rangle} \right] > \\ &\geq -\varepsilon \langle S^k, \mathcal{J}'(u^k) \rangle \left[ 1 - \frac{\varepsilon L A_2}{2A_3} \right]. \end{aligned}$$

(by Lemma 1 and 2)

$$\begin{aligned} &\geq \varepsilon A_3 \|\mathcal{J}'(u^k)\|^2 \left[ 1 - \frac{\varepsilon L A_2}{2A_3} \right] && \text{(by Lemma 2)} \\ &\geq \varepsilon A_3 \|\mathcal{J}'(u^k)\|^2 \left[ 1 - \frac{2A_3 L}{2A_2 L(a+1)} \cdot \frac{A_2}{A_3} \right] = \\ &= \frac{\varepsilon a A_3}{a+1} \|\mathcal{J}'(u^k)\|^2 = A_4 \|\mathcal{J}'(u^k)\|^2 > 0, \end{aligned}$$

where  $A_4 = \frac{\varepsilon a A_3}{a+1} = \text{constant} > 0$ .

Consequently, combining it with the condition of « cleft-overstep » (5) we have

$$\begin{aligned} \mathcal{J}(u^k) - \mathcal{J}(u^k + \alpha_{k+1} S^k) &\geq \mathcal{J}(u^k) - \mathcal{J}(u^k + \varepsilon S^k) > \\ &\geq A_4 \|\mathcal{J}'(u^k)\|^2 > 0 \end{aligned}$$

It follows that the sequence of numbers  $\{J(u^k)\}_{k \rightarrow \infty}$  is monotonically decreasing. Since  $J(u)$  is bounded from below, it follows from the Bolzano-Weierstrass theorem that the sequence of  $\{u^k\}$  is convergent. Moreover

$$\lim_{k \rightarrow \infty} (\mathcal{J}(u^k) - \mathcal{J}(u^{k+1}))$$

At the same time

$$\lim_{k \rightarrow \infty} \|\mathcal{J}'(u^k)\| = 0.$$

It means that the sequence  $\{u^k\}$  always converges to a critical point.

By the hypothesis that  $J(u)$  is a convex and continuous function, the set  $M(u^0) = \{u \mid J(u) \leq J(u^0)\}$  is bounded. In a similar way as for the proof of Theorem 2 in [1] we obtain a minimizing sequence for  $J(u)$  and if  $J(u)$  has a unique minimum point then  $\lim_{k \rightarrow \infty} u^k = u^*$

#### 4.4 Proof of theorem 2.

Using the results in the proof of Theorem [1] we have

$$\mathcal{J}(u^k) - \mathcal{J}(u^{k+1}) \geq A_4 \|\mathcal{J}'(u^k)\|^2$$

where

$$A_4 = \frac{\varepsilon a A_3}{a+1} = \text{constant} > 0$$

We denote  $a_k = \mathcal{J}(u^k) - \mathcal{J}^*$ . If  $J(u)$  is convex then

$$a_k = \mathcal{J}(u^k) - \mathcal{J}^* \leq \langle \mathcal{J}'(u^k), u^k - u^* \rangle \leq \|\mathcal{J}'(u^k)\| \cdot \|u^k - u^*\| < D \|\mathcal{J}'(u^k)\|$$

where

$$D = \sup_{u, v \in M(u^0)} \|u - v\|$$

It follows that

$$a_k = a_{k+1} \geq \frac{A_4}{D^2} \cdot a_k^2$$

and by Lemma 2 of §1, Chapter 2 in [2] (page 65), we obtain

$$a_k < \frac{k_0 + 1}{A_4} \cdot D^2 \cdot \frac{1}{k} = \frac{D^2}{A_4} \cdot \frac{1}{k}, \text{ for } k = 0. \text{ If } J(u) \text{ is a strongly convex}$$

function then by Theorem 6 of §1 Chapter 2 in [3] (page 60) we have :

$$a_k - a_{k+1} \geq A_4 \|\mathcal{J}'(u^k)\|^2 \geq \mu A_4 a^k, \mu > 0.$$

Therefore

$$a_{k+1} \leq a_k (1 - A_4 \mu) = a_k q, \quad q = 1 - A_4 \mu.$$

We thus obtain

$$a_{k+1} \leq a_0 q^k, \quad \mathcal{J}(u^{k+1}) - \mathcal{J}^* \leq (\mathcal{J}(u^0) - \mathcal{J}^*) q^{k+1}$$

$$\|u^{k+1} - u^*\|^2 \leq \frac{2}{\mathcal{X}} (\mathcal{J}(u^{k+1}) - \mathcal{J}^*) \leq \frac{2}{\mathcal{X}} \cdot (\mathcal{J}(u^0) - \mathcal{J}^*) q^{k+1}, \quad \text{where } \mathcal{X} > 0.$$

The proof of Theorem 2 is complete.

## 5. EXPERIMENTAL COMPUTATION

The proposed algorithm was coded in FORTRAN and tested on a Minicomputer CM4 for 5 different examples.

**Example 1.** The Rozenbrock function [4, 5]

$$\mathcal{J}_1(u) = 100(u_2 - u_1^2)^2 + (1 - u_1)^2$$

The starting point  $u^0 = (-1, 2; 1)$ ,  $\mathcal{J}_1(u^0) = 24,2$ .

The minimum point  $u^* = (1, 0; 1; 1, 0)$ ,  $\mathcal{J}_1(u^*) = 0$ .

The results of computation are given in Table 1.

**Example 2.** The Wood function [4, 5]

$$\begin{aligned} \mathcal{J}_2(u) = & 100(u_2 - u_1^2)^2 + (1 - u_1)^2 + 90(u_4 - u_3^2)^2 + (1 - u_3)^2 + \\ & + 10,1[(1 - u_2)^2 + (1 - u_4)^2] + 19,8(1 - u_2)(1 - u_4). \end{aligned}$$

The starting point  $u^0 = (-3; -1; -3; -1)$ ,  $\mathcal{J}_2(u^0) = 19192$ .

The minimum point  $u^* = (1; 1; 1; 1)$ ,  $\mathcal{J}_2(u^*) = 0$ .

The results of computation are given in Table 2.

**Example 3.** The Powell function [4, 5]

$$\mathcal{J}_3(u) = (u_1 - 10u_2)^2 + 5(u_3 - u_4)^2 + (u_2 - 2u_3)^4 + 10(u_1 - u_2)^4$$

The starting point  $u^0 = (3; -1; 0; 1)$ ,  $\mathcal{J}_3(u^0) = 215$ .

The minimum point  $u^* = (0; 0; 0; 0)$ ,  $\mathcal{J}_3(u^*) = 0$ .

The results of computation are given in Table 3.

**Example 4.** The Poliak function [4, 5]

$$\mathcal{J}_4(u) = \sum_{i=1}^{10} (e^{-0,2i} + 2e^{-0,4i} - u_1 e^{-0,2iu_2} - u_3 e^{-0,2iu_4})^2$$

The starting point  $u^0 = (0,5; 0; 2,5; 3); \mathcal{J}_4(u^0) = 0,544$ .

The minimum point  $u^* = (1; 1; 2; 2); \mathcal{J}_4(u^*) = 0$ .

The results of computation are given in Table 4

**Example 5.** The Nurminski function [3]

$$\mathcal{J}_5(u) = \max \left\{ |u_2|, \frac{u_1^2}{(1+u_2^2)^2} \right\}.$$

The starting point  $u^0 = (7; 7); \mathcal{J}_5(u^0) = 7$ .

The minimum point  $u^* = (0; 0); \mathcal{J}_5(u^*) = 0$ .

The results of computation are given in table 5.

In Tables 1–5 we denote by  $N$  the times of computing the objective function  $J(u)$  and by  $\Delta J = J(u)_N - J(u^*)$  the corresponding different between  $J(u)_N$  and its optimal value  $J(u^*)$ ;

In these tables we also give the comparison of the efficiency of the algorithm of «cleft-overstep» by perpendicular direction (A. D. O. S. P.) with three known algorithms:

– the steepest descent algorithm (S. C. A.)

– the conjugate gradient algorithm (C. G. A.)

– the transformed polytope algorithm (T. P. A.)

In our algorithm (A. C. O. S. P.) we choose  $\varepsilon = 0; \varepsilon_1 = 0,05; \varepsilon_2 = 0,95; \alpha = 1; \gamma_1 = 10^{-2}; \gamma = 0,618$ .

The process of finding the «cleft-overstep» length is as follows: we denote

$$g_k(\alpha) = \mathcal{J}(u^{k-1} + \alpha S^{k-1}).$$

Step 0. Pose  $\alpha_a = 0, \alpha_b = \alpha_{k-1}, k = 1, 2, \dots, \alpha_0 = 0,5$ .

Step 1. Calculate the value  $g_k(\alpha_a)$  and  $g_k(\alpha_b)$ .

a) If  $g_k(\alpha_b) < g_k(\alpha_a)$  then put  $\alpha_a := \alpha_b, \alpha_b = 2\alpha_b$  and go back to step 1.

b) If  $g_k(\alpha_b) \leq g_k(\alpha_a)$  the go to step 2.

Step 2.

a) If  $g_k(\alpha_b) \leq g_k(\varepsilon)$  then put  $\alpha_k := \alpha_b$  and stop the process of finding the «cleft-overstep» length.

b) If  $g_k(\alpha_b) > g_k(\varepsilon)$  then go to step 3.

Step 3. Check the inequality  $|\alpha_b - \alpha_a| \leq \gamma_1$

a) If  $|\alpha_b - \alpha_a| \leq \gamma_1$  then put  $\alpha_k := \alpha_a$  and stop the process of finding the « cleft—overstep » length.

b) If  $|\alpha_b - \alpha_a| > \gamma_1$  then go to step 4.

Step 4. Calculate  $\alpha = \alpha + \gamma (\alpha_b - \alpha_a)$  and  $g_k(\alpha)$

a) If  $g_k(\alpha_a) < g_k(\alpha) \leq g_k(\varepsilon)$  set  $\alpha_k := \alpha$  and stop the process of finding the cleft-overstep » length.

b) If  $g_k(\alpha) \leq g_k(\alpha_a)$  then put  $\alpha_a := \alpha$  and go back to step 3.

c) If  $g_k(\alpha) > g_k(\varepsilon)$  then put  $\alpha_b := \alpha$  and go back to step 3.

Table 1.

A.C.O.S.P.		S. D. A.		C. G. A.		T. P. A.	
N	$\Delta J$	N	$\Delta J$	0	$\Delta J$	N	$\Delta J$
0	$0.242 \times 10^2$	0	$0.242 \times 10^2$	0	$0.242 \times 10^2$	0	$0.242 \times 10^2$
75	$0.4 \times 10^0$	13140	$0.4 \times 10^{-2}$	546	$0.13 \times 10^0$	86	$0.9 \times 10^0$
169	$0.13 \times 10^{-2}$	26140	$0.67 \times 10^{-3}$	981	$0.18 \times 10^{-9}$	169	$0.81 \times 10^{-3}$
262	$0.33 \times 10^{-6}$	31782	$0.33 \times 10^{-3}$			216	$0.5 \times 10^{-7}$
279	$0.51 \times 10^{-7}$						

Table 2.

A. C. O. S. P.		S. D. A.		C. G. A.		T. P. A.	
N	$\Delta J$	N	$\Delta J$	N	$\Delta J$	N	$\Delta J$
0	19192	0	19192	0	19192	0	19192
413	$0.12 \times 10^{-2}$	842	$0.79 \times 10^1$	120	35 . I	252	$0.16 \times 10^1$
810	$0.15 \times 10^{-3}$					471	$0.26 \times 10^{-1}$
1029	$0.68 \times 10^{-6}$	From here the algorithms are not stabilized and do not converge.				58	$0.11 \times 10^{-5}$
1462	$0.15 \times 10^{-6}$						

Table 3.

A. C. O. P.		S. D. A.		C. G. A.		T. P. A.	
N	$\Delta J$	N	$\Delta J$	N	$\Delta J$	N	$\Delta J$
0	$0.215 \times 10^2$	0	$0.215 \times 10^2$	0	$0.215 \times 10^2$	0	$0.215 \times 10^2$
300	$0.56 \times 10^{-3}$	6326	$0.84 \times 10^{-3}$	258	$0.60 \times 10^{-1}$	83	$0.41 \times 10^{-2}$
622	$0.56 \times 10^{-4}$	12326	$0.25 \times 10^{-3}$	545	$0.14 \times 10^{-2}$	164	$0.21 \times 10^{-5}$
955	$0.16 \times 10^{-5}$	16466	$0.15 \times 10^{-3}$	1024	$0.23 \times 10^{-4}$	221	$0.14 \times 10^{-8}$
1049	$0.1 \times 10^{-5}$			1200	$0.80 \times 10^{-6}$		

Table 4.

A.C.O.P		S.D.A.		C.G.A.		T.P.A	
N	$\Delta J$	N	$\Delta J$	N	$\Delta J$	N	$\Delta J$
0	0.514	0	0.544	0	0.544	0	0.544
1051	$0.24 \times 10^{-5}$	844	$0.18 \times 10^{-3}$	607	$0.25 \times 10^{-3}$	118	$0.29 \times 10^{-3}$
2062	$0.10 \times 10^{-6}$	1340	$0.77 \times 10^{-5}$	1218	$0.34 \times 10^{-4}$	231	$0.20 \times 10^{-3}$
2905	$0.10 \times 10^{-6}$	3160	$0.45 \times 10^{-5}$	1310	$0.29 \times 10^{-4}$	318	$0.20 \times 10^{-3}$
						The paralysis occurs	

Table 5.

A. C. O. P.		S. D. A.		C. G. A.		T. P. A.	
N	$\Delta J$	N	$\Delta J$	N	$\Delta J$	N	$\Delta J$
0	$0.70 \times 10^1$	0	$0.70 \times 10^1$	0	$0.70 \times 10^1$	0	$0.70 \times 10^1$
82	$0.92 \times 10^{-3}$	541	$0.20 \times 10^1$	The Algorithm not stabilized		90	$0.28 \times 10^1$
173	$0.15 \times 10^{-5}$	1061	$0.20 \times 10^1$			198	$0.28 \times 10^1$
210	$0.59 \times 10^{-6}$	The paralysis occurs ;		225	$0.16 \times 10^{-1}$	The paralysis occurs.	
				308	$0.41 \times 10^{-3}$		

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