COMBINED NON-QUADRATIC MODELS AS A BASIS FOR CG-A LGORITHMS

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ABSTRACT

In this paper, a new extended (CG) algorithms is proposed. It is in fact, a particular type of the Conjugate Gradient (CG) method which employs non-quadratic rational model, and based on inexact line searches. The Flecther and Reeves restarting criterion was employed to the standard and New versions and gave dramatic savings in computational time. The new algorithms is were promising in general, seven non linear tests function with different versions were used.

ربط نماذج غير تربيعية كأساس الخوارزمية في التدرج المترافق

الملخص

في هذا البحث jم استحداث خوارزمية جديدة موسعة في مجال التدرج المترافق لربط نماذج غير تربيعية .والنموذج الجديد نموذج نسبي غير تربيعي معتمد على خطوط بحث غير تامة . ولقد تم استعمال وسيلة استرجاع Fletcher Barac على خطوط بحث غير تامة . ولقد تم استعمال وسيلة استرجاع and Reeves الزمن المطلوب للحل. اثبتت الحسابات العددية اكفاءة الخوارزمية الجديدة مقارنة بالأخرى وباستعمال دوال غير خطية وبأبعاد مختلفة .

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1.Introduction:

Conjugate gradient (CG) algorithms form a class of CGalgorithms for minimizing a general differentiable function f(x) $x \in \mathbb{R}^n$. whose gradient g (x) can be calculated , are based on the following concept of conjugacy:

If Q is a positive definite symmetric $n \times n$ matrix, then the directions d_1, d_2, \dots, d_n where $d_k \neq 0$ for k=1,2,...,n, are mutually Q-conjugate if

 $d_i^T Q d_k = 0$ for $i \neq k$

The classical algorithm in this category proposed by Flectcher and Reeves (9) and is based on the iterative scheme:

 $x_{k+1} = x_k + \lambda_k d_k$, k = 1, 2, ..., nWhere the scalar λ_k is the smallest positive local minimizer of the One dimensional problem

 $\min_{\lambda} f(x_k + \lambda d_k)$

is a search direction generated by the equations : d_k and

for
$$k = 1, 2, ..., n$$

 $d_1 = -g_1,$
 $d_{k+1} = -g_{k+1} + \beta_k d_k,$
 $\beta_k = g_{k+1}^T y_k / d_k^T y_k$

If the method is applied to the quadratic function

$$q(x) = \frac{1}{2}x^T Q x$$

2. Extended Conjugate Gradient (ECG) method:

A more general model than the quadratic one is proposed in this paper as a basis for a CG algorithm. If q(x) is a quadratic function, then a function f is defined as a nonlinear scaling of q(x) if the following condition holds :

f = F(q(x)), dF/dq = F' > o and q(x) > 0(1) Where x* is the minimizer of q(x) with respect to x Spedicate().

|--|

The following properties are immediately derived from the above condition:

i) Every contour line to q(x) is a contour line of f.

If f.

If x^* is a minimizer of q(x), then it is a minimizer of

That x^* is a global minimum of q(x) does not necessarily mean that it is a global minimum of f.

Various authors have puplished related works in the area: A conjugate method which minimizes the function

 $f(x) = (q(x))^{\rho}$, and $x \in R^n$ in at most step has been described by Fried [10].

Another special case, namely $F(q(x)) = \varepsilon_1 q(x) + \frac{1}{2} \varepsilon_2 q^2(x)$

Where ε_1 and ε_2 are scalars, has been investigated by Boland & Kowalik [7].

Another model has developed by Tassopoulos and Storey ,[14] as follows:

 $F(q(x) = \varepsilon_1 q(x) + 1/\varepsilon_2 q(x): \varepsilon_2 > 0$ AL-Assady in [3] developed another model as follows (F(q(x)) = In(q(x))

Al-Bayati ,[1] has been developed a new rational models which is defined as follows: $F(q(x)) = \varepsilon_1 q(x)/1 - \varepsilon_2 q(x), \varepsilon_2 < 0$.

Also Al-Bayati ,[2] developed an extended CG algorithm which is based on a general logarithmic model

 $F(q(x) = log(\epsilon q(x) - 1), \epsilon > 0$

Al-Assady &Huda,[5] described there ECG algorithm which is based on the natural log function for the rational q(x) function

$$\mathbf{F}(\mathbf{q}) = \log \left[\frac{\mathcal{E}_1 q(x)}{\mathcal{E}_2 q(x) + 1} \right], \varepsilon_2 < \mathbf{0}$$

ii)

3.CONJUGATE GRADIENT METHOD WITW INEXACT LINE SEARCH:

In order to improve the local rate of convergence and the efficiency of the traditional CG-method several well-Know methods are discussed in this area. A mong these methods Sloboda (13) defines a new generalized CG.a lgorithm for minimizing a strictly convex function of the general form f(x) = F(q(x)).....(2)

We now list out-lines of sloboda extended CG. method : Algorithm (sloboda 1980)

Step (1): set k=1; $\overline{g}_k = g_k$ and $d_k = -\overline{g_k}$

Step (2): compute λ_k by exact line search and $x_{k+1} = x_k + \lambda_k d_k$

Step (3): compute $g_{k+1/2}^+ = g(x_k + \lambda_k d_k/2)$

Step (4): Test for convergence if achieved stop. If not continue

Step (5): If k=0 mod (n) go to step (1) else continue

Step (6): compute $\overline{g_{k+1}} = w_k g_{k+1}^+ - \overline{g_{k+1}}$ where

 $w_{k} = d_{k}^{T} \overline{g_{k}} / d_{k}^{T} g_{k+1/2}^{+}$ If $\overline{g_{k+1}} = 0$ set i=i+1 go to step (1)

Step (7): $d_{k+1} = -\overline{g_{k+1}} + \beta_k d_k$; $\beta = (\overline{g_{k+1}} - \overline{g_k})\overline{g_{k+1}} / d^T (\overline{g_{k+1}} - g_k)$ Step (8): set k=k+1 and go to step (2)

Step (9): If k. EQ .n go to Step (1). If not continue.

4. The Derivation p_i:

The implementation of the extended CG method has been performed for general function F(q(x) of the form of equation(2). The unknown quantities P_i were expressed in terms of available quantities of the algorithm .The authors , introduced in [4] a new model , which can be written as

The ne
$$\sin\left(\frac{\varepsilon_1 q(x) + 1}{\varepsilon_2 q(x)}\right)$$

model can now be written

as

$$\mathbf{f}(\mathbf{x}) = \mathbf{F}(\mathbf{q}(\mathbf{x})) \left(\frac{\varepsilon_1 q(x) + 1}{\varepsilon_2 q(x)}\right)$$

Solving equation (2) for q

$$\begin{aligned} & \operatorname{Sin}^{-1} f(x) \left(\frac{\varepsilon_1 q(x) + 1}{\varepsilon_2 q(x)} \right) \\ & = \frac{\ln \left[\operatorname{if}(x) + \sqrt{1 - f(x)^2} \right]}{\varepsilon_2 q(x)} \quad \frac{\varepsilon_1 q(x) + 1}{\varepsilon_2 q(x)} \quad \int_{\varepsilon_2}^{1} \ln \left[\operatorname{if}(x) + \sqrt{1 - f(x)^2} \right] - \varepsilon_1 \end{aligned}$$

And using the expression for $\mathbf{p_i} = \mathbf{f'_{i-1}} / \mathbf{f'_i}$

$$\rho_{i} = -\frac{\cos(\varepsilon_{1}q_{i-1} + 1/\varepsilon_{2}q_{i-1}) \left(\frac{-1}{\varepsilon_{2}q_{i-1}}\right)}{\cos(\varepsilon_{1}q_{i} + 1/\varepsilon_{2}q_{i}) \left(\frac{-1}{\varepsilon_{2}q_{i}^{2}}\right)}.$$

From the above equation we have

$$\rho_{i} = \begin{bmatrix} \left[\left[if_{i-1} + \sqrt{1 - f_{i-1}^{2}} \right]^{2} + 1 \right] \left[\ln(if_{i-1} + \sqrt{1 - f_{i-1}^{2}}) - \frac{\varepsilon_{1}}{\varepsilon_{2}} \right]^{2} \\ \frac{if_{i-1} + \sqrt{1 - f_{i-1}^{2}}}{\left[\frac{if_{i-1} + \sqrt{1 - f_{i-1}^{2}}}{\left[\frac{if_{i-1} + \sqrt{1 - f_{i-1}^{2}}}{if_{i} + \sqrt{1 - f_{i}^{2}}} \right]^{2} \\ \frac{if_{i-1} + \sqrt{1 - f_{i-1}^{2}}}{if_{i} + \sqrt{1 - f_{i-1}^{2}}} \end{bmatrix}$$

In terms of the known quantities such a function and gradient values, from

$$g_{i} = F'_{i}Q(x_{i} - x^{*})$$

$$g_{i-1} = F'_{i-1}Q(x_{i-1} - x^{*})$$

We are Q in

Where Q is the Hessian Matrix and x^* is the minimum point, we have :

$$\boldsymbol{\rho}_{i} = \begin{bmatrix} \left[\left[if_{i-1} + \sqrt{1 - f_{i-1}^{2}} \right]^{2} + 1 \right] \left[\ln\left(if_{i-1} + \sqrt{1 - f_{i-1}^{2}} \right) - \frac{\varepsilon_{1}}{\varepsilon_{2}} \\ \frac{if_{i-1} + \sqrt{1 - f_{i-1}^{2}}}{\left[\left[if_{i} + \sqrt{1 - f_{i}^{2}} \right]^{2} + 1 \right] \left[\ln\left(if_{i} + \sqrt{1 - f_{i}^{2}} \right) - \frac{\varepsilon_{1}}{\varepsilon_{2}} \right]^{2}}{if_{i} + \sqrt{1 - f_{i}^{2}}} \end{bmatrix}$$

Furthermore

$$g_{i-1}^{T}(x_{i} - x^{*}) = g_{i-1}^{T}(x_{i-1} + \lambda_{i-1}d_{i-1} - x^{*})$$
$$= g_{i-1}^{T}(x_{i-1} - x^{*}) + \lambda_{i-1}g_{i-1}^{T}d_{i-1}....(3)$$

$$g_{i}^{T}(x_{i} - x^{*}) = g_{i}^{T}(x_{i} + \lambda_{i}d_{i} - x^{*})$$
$$= g_{i}^{T}(x_{i} - x^{*})$$

Since $g_i^T d_{i-1} = 0$ Therefore, we can express ρ_i us follows: -

$$\rho_{i} = \frac{g_{i-1}^{T}(x_{i-1} + \lambda_{i-1}d_{i-1} - x^{*})}{g_{i}^{T}(x - x^{*})}$$

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From (3) and (4), it follows that : $\dots (4)$

$$\rho_{i} = \rho_{i} \left[\frac{q_{i-1}}{q_{i}} \right] + \lambda_{i-1} g_{i-1}^{T} d_{i-1} / 2F_{i}' q_{i}$$

Where

$$q \quad and f' = \frac{\left[\left[if + \sqrt{1 - f^2}\right]^2 + 1\right] - \varepsilon_2 \left[\ln\left(if + \sqrt{1 - f^2}\right) - \frac{\varepsilon_1}{\varepsilon_2}\right]^2}{2\left[if + \sqrt{1 - f^2}\right]}$$

The quantities q_{i-1}/q_i And $J_i q_i$ can be rewritten as :

$$\frac{q_{i-1}}{q_i} = \frac{\ln\left[if_i + \sqrt{1 - f_i^2}\right] - \frac{\varepsilon_1}{\varepsilon_2}}{\ln\left[if_{i-1} + \sqrt{1 - f_{i-1}^2}\right] - \frac{\varepsilon_1}{\varepsilon_2}}$$

$$f_{i}'q_{i} = \frac{\left[if_{i} + \sqrt{1 - f_{i}^{2}}\right]^{2} + 1\left[ln(if_{i} + \sqrt{1 - f_{i}^{2}}) - \frac{\varepsilon_{1}}{\varepsilon_{2}}\right]}{2[if_{i} + \sqrt{1 - f_{i}^{2}}]}$$

From the definition of ρ_i we have :

$$\frac{\left[\left[if_{i-1}^{2}+\sqrt{1-f_{i-1}^{2}}\right]^{2}+1\right]\left[\ln\left(if_{i-1}^{2}+\sqrt{1-f_{i-1}^{2}}\right)-\frac{\varepsilon_{1}}{\varepsilon_{2}}\right]^{2}}{if_{i-1}^{2}+\sqrt{1-f_{i-1}^{2}}} = \frac{\left[if_{i}^{2}+\sqrt{1-f_{i}^{2}}\right]^{2}+1\right]\left[\ln\left(if_{i}^{2}+\sqrt{1-f_{i}^{2}}\right)-\frac{\varepsilon_{1}}{\varepsilon_{2}}\right]^{2}}{if_{i}^{2}+\sqrt{1-f_{i}^{2}}} = \frac{if_{i}^{2}+\sqrt{1-f_{i}^{2}}}{if_{i}^{2}+\sqrt{1-f_{i}^{2}}} = \frac{if_{i}^{2}+1}{if_{i}^{2}+\sqrt{1-f_{i}^{2}}} = \frac{if_{i}^{2}+1}{if_{i}^{2}+\sqrt{1-f_{i}^{2}}}} = \frac{if_{i}^{2}+1}{if_{i}^{2}+1}} = \frac{if_{i}^{2}+1}{if_{i}^{2}+1}} = \frac{if_{i}^{2}+$$

$$\begin{bmatrix} \underbrace{\left[\left[if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right]^{2}+1\right]\left[\ln\left(if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right)-\frac{\varepsilon_{1}}{\varepsilon_{2}}\right]}{if_{i-1}+\sqrt{1-f_{i-1}^{2}}} \\ \frac{\underbrace{\left[if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right]^{2}+1\left[\ln\left(if_{i}+\sqrt{1-f_{i}^{2}}\right)-\frac{\varepsilon_{1}}{\varepsilon_{2}}\right]^{2}}{if_{i}+\sqrt{1-f_{i}^{2}}} \\ \end{bmatrix} - \frac{(\lambda_{i-1}g_{i-1}^{T}d_{i-1})}{\left[\left[if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right]^{2}+1\right]\left[\ln\left(if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right)-\frac{\varepsilon_{1}}{\varepsilon_{2}}\right]}{if_{i}+\sqrt{1-f_{i}^{2}}} \\ \end{bmatrix} - \frac{(\lambda_{i-1}g_{i-1}^{T}d_{i-1})}{\left[\left[if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right]^{2}+1\right]\left[\ln\left(if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right)-\frac{\varepsilon_{1}}{\varepsilon_{2}}\right]}{if_{i-1}+\sqrt{1-f_{i-1}^{2}}} \\ \end{bmatrix}$$

using the following transformation:

$$\frac{\left[if_{i}+\sqrt{1-f_{i}^{2}}\right]^{2}+1}{if_{i}+\sqrt{1-f_{i}^{2}}} = x, \qquad \ln\left[if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right] - \frac{\varepsilon_{1}}{\varepsilon_{2}} = y$$
$$\ln\left[if_{i}+\sqrt{1-f_{i}^{2}}\right] - \frac{\varepsilon_{1}}{\varepsilon_{2}} = y + w \qquad \text{and} \qquad \ln\left[if_{i}+\sqrt{1-f_{i}^{2}}\right] - \ln\left[if_{i-1}+\sqrt{1-f_{i-1}^{2}}\right] = w$$

 $c = \lambda_{i-1} g_{i-1}^T d_{i-1}$

Then y=cw/xw+c

Therefore

$$\overline{f_{i-1}^{2}} = \frac{\left[\ln \left[if_{i} + \sqrt{1 - f_{i}^{2}} \right] \right] - \ln \left[if_{i} + \sqrt{1 - f_{i}^{2}} \right] \left[-\lambda_{i-1}g_{i-1}d_{i-1} \right] }{\left[if_{i-1} + \sqrt{1 - f_{i-1}^{2}} \right] + 1 \left[\ln \left[if_{i-1} + \sqrt{1 - f_{i-1}^{2}} \right] - \ln \left[if_{i-1} + \sqrt{1 - f_{i-1}^{2}} \right] \right] + \lambda_{i-1}g_{i-1}d_{i-1}}$$

5.New modification for the Sloboda method :

In order to improve the global rate of convergence of minimization algorithms when applied to more general functions than the quadratic variable metric (VM) matrices which may be used to accelerate the CG-algorithm (see for example Al-Byati and Al-assady (6)). In this section, a new expression for the new search direction d_{k+1} of the Sloboda method is suggested which is invariant to non-linear scaling of non-quadratic function. Al-assady and Hassan (4) (to appear) are used to extend the sloboda method.

In use the new suggested algorithms require less vector storage's than the sloboda algorithms.

We now give the outline of the new proposed modifications: New Algorithm:

Step (1): set k=1; $\overline{g}_k = g_k$ and $d_k = -\overline{g_k}$

Step (2): compute λ_k by ELS and $x_{k+1} = x_k + \lambda_k d_k$

Step (3): compute $g_{k+1}^+ = g(x_k + \lambda_k d_k / 2)$

Step (4): Test for convergence if achieved stop.

If not continue

Step (5): If $k=0 \mod (n)$ go to step (1) else continue

Step (6): compute
$$g_{k+1} = w_k g_{k+1}^+ - g_{k+1}$$
 where

$$W_{k} = d_{k}^{T} g_{k} / d_{k}^{T} g_{k+1/2}^{+}$$

If
$$\overline{g_{k+1}} = 0$$
 set I=I+1 go to step (1)

Step (7) compute

$$\boldsymbol{\rho}_{i} = \begin{bmatrix} \underbrace{\left[if_{i-1} + \sqrt{1 - f_{i-1}^{2}} \right]^{2} + 1 \right] \left[\ln\left(if_{i-1} + \sqrt{1 - f_{i-1}^{2}} \right) - \frac{\varepsilon_{1}}{\varepsilon_{2}} \right]^{2}}_{if_{i-1}} + \sqrt{1 - f_{i-1}^{2}} \\ \frac{if_{i-1} + \sqrt{1 - f_{i-1}^{2}}}{\left[\left[if_{i} + \sqrt{1 - f_{i}^{2}} \right]^{2} + 1 \right] \left[\ln\left(if_{i} + \sqrt{1 - f_{i}^{2}} \right) - \frac{\varepsilon_{1}}{\varepsilon_{2}} \right]^{2}}{if_{i}} + \sqrt{1 - f_{i}^{2}} \end{bmatrix}}$$

Step (8): $d_{k+1} = -g_{k+1} + \beta_k d_k$; $\beta = (\overline{\rho_k g_{k+1}} - \overline{g_k})\overline{g_{k+1}} / d^T (\rho_k \overline{g_{k+1}} - g_k)$

Step (9): set k=k+1 and go to step (2)

Step (10): If k. EQ .N go to Step (1)

6. Numerical Results and conclusion :

In order to test the effectiveness of the new algorithms that have been used to extent the Sloboda method, a number of function have been chosen and solved numerically by utilizing the new and established method

The same line search was employed for all the methods. This was the cubic interpolation procedure described in Bunday(8).

It is found that the NEW method which modifies Sloboda algorithm is better than the previous algorithm shown in table.

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Table (1): Which uses the H/S formula, presents a comparison between the results of the NEW methods and the Sloboda method. So we can show that the NEW method has less (NOI) and (NOF) than the classical Sloboda method. The NEW method improves the two measures of performances, vis (NOI) and (NOF) (67.17)% and the (80.25)% for the H/S formula.

Test	N	New	Sloboda
Function	IN	NOI (NOF)	NOI (NOF)
SHALLO	2	7 (20)	9 (23)
	4	7 (21)	8 (21)
	10	10 (30)	8 (20)
DIXON	2	6 (13)	6 (17)
	4	10 (25)	12 (26)
	10	18 (40)	19 (41)
POWELL	20	49 (126)	60 (158)
	100	120 (270)	112 (384)
	200	178 (410)	119 (251)
WOOD	100	102 (210)	205 (423)
	200	150 (310)	402 (817)
	400	105 (214)	103 (213)
NON- DIAGONL	4	20 (60)	23 (63)
	40	21 (61)	21 (61)
	400	16 (45)	23 (67)
CANTRAL	100	35 (230)	43 (347)
	200	47 (270)	46 (393)
	400	42 (180)	47 (410)
WOLFE	4	11(26)	12(27)
	20	30(71)	35(71)
Total	NOI (NOF)	837 (2560)	1246 (3190)

Table: Comparison between the different ECG – methods by using H/S formula.

Appendix

1.Generalized Powell Functions: $F(x) = \sum_{i=1}^{n/4} (x_{4i-9} + 10x_{4i-2})^2 + 5(x_{4i-1} - x_{4i})^2 + (x_{4i-2} - 2x_{4i-1})^4 + 10(x_{4i-9} - x_{4i})^4$

$$\mathbf{x}_0 = (3,1,0,1)^{\mathrm{T}}$$

2. Generalized Cantreal Functions: $F(x) = \sum_{i=1}^{n/4} \left[\exp(x_{4i-3}) - x_{4i-2} \right]^2 + 100(x_{4i-2} - x_{4i-1})^6 + \left[(a \tan(x_{4i-1} - x_{4i})) \right]^4 + x_{4i-3}^8$

$$x_0 = (1, 2, 2, 2)^T 3.Wo$$

od Functions:

$$F(x) = \sum_{i=1}^{n/4} 100(x_{4i-2} + x_{4i-3}^2)^2 + (1 - x_{4i-3})^2 + 90(x_{4i} - x_{4i-1}^2)^2 + (1 - x_{4i-1})^2 + 1.0$$

$$x_0 = (-3, -1, -3, -1)^T 4$$

.Non-Diagonal Functions:

$$F(x) = \sum_{i=2}^{n} 100(x_i - x_0^2)^2 + (1 - x_i)^2$$

$$x_0 = (-1, ...,)^T$$

5.Dixon Functions:

$$F(x) = (1 - x_1)^2 + (1 - x_0)^2 + \sum_{i=2}^{9} (x_i - x_{i-1})$$

 $x_0 = (-1, \dots,)^T$

6.Wolfe Functions:

$$F(x) = (-x_1(3 - x_1/2) + 2x_2 - 1)^2 + \sum_{i=1}^{n-1} (x_{i-1} - x_i(3 - x_i/2) + 2x_{i+1} - 1)^2 + (x_{n-1} - x_n(3x_n/2) - 1)^2$$
$$x_0 = (-1, \dots,)^T$$

7.Shallo Functions:

$$F(x) = \sum_{i=1}^{n/2} (x_{2i-1}^2 - x_{2i})^2 + (1 - x_{2i-1})^2$$

x₀ = (-2)

$$x_0 = (-2, -2, \dots)^T$$

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