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Advanced algorithmic approach to optimization using MATLAB programming

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Abstract

This paper introduces a novel conjugate gradient (CG) algorithm approach for unconstrained optimization problems: the (MOD) method under Wolfe condition. The primary argument is that the (MOD) approach can lower function evaluation, CPU time, and iterations. A MATLAB program (version R2016a) and a comparison of numerical results with two popular approaches, the SCG method and the PRP method, are used to illustrate this. When a suitable line search is suggested and the right conditions are met, the proposed method has the sufficient descent property. We construct both the global convergence and the well-defined algorithm. These results show that the new strategy performs better than the traditional algorithms.

Keywords: Descent property, conjugate gradient method, global convergence, optimization problems.

Introduction

Different approaches can be used to solve large-scale unconstrained optimization issues. Backgroundique, which takes the following form, is one efficient way to solve unconstrained optimization problems:

$$\min_{x \in R^n} f(x), \quad (1)$$

s.t. $F: R^n \rightarrow R$ this continuously differentiable function. From the initial point $x_0 \in R^n$, the iterative sequence $\{x_k\}$ is generated to solution this problem by the recurrence

$$x_{k+1} = x_k + \alpha_k d_k, k \in N \quad (2)$$

and $\alpha_k > 0$ is obtained through a line search and d_k is a search direction given by:
In addition the space R^i is vector space with Euclidean norm $\| \cdot \|$ defined as follows ^[1]:

$$\|x\| = \sqrt{\sum_{t=1}^i (x_t)^2}; \forall x \in R^i. \quad (3)$$

In this work, we aim to introduce a new two-term conjugate gradient approach to solve large-scale equations due to the limited memory and simplicity. The authors introduced numerous techniques to solve various optimization and reliability problems (see) ^[2-6]. The suggested method satisfied both the steepest descent property and the Wolfe condition formula for global convergence.

The New Suggested Algorithm (MOD)

In this hand, we describe the framework of the suggested approach and satisfies a nice descent property. We used the new technique with (CGM) for solving a large scale problems of unconstrained optimization ^[7] constructed appropriate hyperplane $\mathcal{H}_k$ where strictly separates x_k from the solution set of problem (1) i.e.

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$$\mathcal{H}_k = \{x \in R^n \mid F(z_k)^T(x - z_k) = 0\}.$$

Dependent on Solodov and Svaiters advised total the other iteration point x_{k+1} is constructed by projecting x_k onto $\mathcal{H}_k$ that is x_{k+1} is determined by:

$$x_{k+1} = x_k - \frac{F(z_k)^T(x_k - z_k)}{\|F(z_k)\|^2} F(z_k), \quad (4)$$

the new search direction of our method can be computed by

$$d_{k+1} = \begin{cases} -F_k + \beta_k^{MOD} y_{k-1} \xi_k d_{k-1}, & \forall k \geq 1 \\ -F_k & \forall k = 0 \end{cases} \quad (5)$$

Where

$$s_k = x_k - x_{k-1}, y_{k-1} = F_k - F_{k-1},$$

$$\xi_k = \frac{y_{k-1} s_k F_k d_{k-1}}{\|y_{k-1}\| \|d_{k-1}\|^2} + \frac{F_k^T y_{k-1} d_{k-1}}{\|y_{k-1}\| \|d_{k-1}\|^2}$$

$$\beta_k^{MOD} = \frac{\|y_{k-1}\| \|d_{k-1}\|^2}{d_{k-1}^T s_k F_k y_{k-1} + F_k^T d_{k-1} y_{k-1}}. \quad (6)$$

According to (4), (5), and (6), one appealing feature of our algorithm is that Conversely, according to (2), (5), and (6), the value of d_k as determined by our method nearly satisfies the descent condition, i.e. we have thus d_k determined by the method almost holds the descent condition i.e.

$$\begin{aligned} d_k^T F_k &= -\|F_k\|^2 + \frac{\|y_{k-1}\| \|d_{k-1}\|^2}{\|d_{k-1}\| \|s_k\| \|F_k\|^2 \|y_{k-1}\| + \|d_{k-1}\| \|F_k\|^2 \|y_{k-1}\|} \\ &= -\|F_k\|^2. \end{aligned}$$

Therefore, the direction d_k determined by our technique usually holds the sufficient descent condition such that

$$F_k^T d_k \leq -c \|F_k\|^2, \forall k \geq 0. \quad (7)$$

Where $c = 1$.

The steps of a new algorithm of the proposed method are as follows:

The algorithm for conjugate gradient projection (MO4)

1. The parameters $\gamma, \tau > 0$ and $\rho, \sigma \in [0, 1]$ are provided, along with the starting point $x_0 \in R^n$.

Set $d_0 = -F_0, k = 0$;
If $\|F(x_k)\| \leq \varepsilon$ break.

2. Let $\alpha_k = \max_{i \in \{0, 1, 2, \dots\}} \{\rho_i \mid \alpha_{k-1}, i=0, 1, 2, \dots\}$ be produced by a Wolfe condition.

$$\begin{aligned} f(x_k + \alpha_k d_k) &\leq f(x_k) + \rho \alpha_k F_k^T d_k, \\ F(x_k + \alpha_k d_k)^T d_k &\leq \sigma F_k^T d_k, \quad (8) \end{aligned}$$

3. Set $z_k = x_k + \alpha_k d_k$. and calculate x_{k+1} by

$$\begin{aligned} x_{k+1} &= P_\Omega[x_k - \xi F(z_k)], \text{ where } \xi \\ &= \frac{F(z_k)^T(x_k - z_k)}{\|F(z_k)\|^2}. \end{aligned}$$

4. If $\|F(x_k)\| \leq \varepsilon$ break. therefore calculate d_{k+1} by (5).
5. Put $k = k + 1$, and return to (2).

Remark (A)

According to the above discussion, in our method, the search Direction d_k holds (7) is a sufficient descent direction of f at iteration x_k . Also, by (8) thus

$$\|d_k\| \geq \|F_k\|, k \in N \quad (9)$$

This means the denominators of β_k^{MOD} and ξ_k are greater than zero usually when $\|F_k\| = 0$ does not hold. This implies that these parameters are well defined.

The New Method's Global Convergence

To examine the new method's global analysis, we need to make a few assumptions.

Assumptions (B)

- i) The function $f(x)$ is continuous on the level set R^n , bounded below, and differentiable in a neighborhood N of the level set. $\varpi(x_0) = \{x \in R^n \mid f(x) \leq f(x_0)\}$ at x_0 .
- ii) The mapping $F(x)$ is Lipschitz continuous i.e. $\exists L > 0$ s.t.
 $\|F(x) - F(y)\| \leq L\|x - y\|$, for all $x, y \in N$. (10)

By using the Assumptions (10) imply that $\exists U > 0$ such that

$$\|F(x)\| \leq U \quad \forall x \in \varpi. \quad (11)$$

We assume, at most, that Assumptions (B) are satisfied in the final section of this work. Furthermore, we assume that $F_k \neq 0, \forall k \geq 0$. In order to analyze the globally convergent, we work to determine the selection of α_k for all that d_k created by the new technique holds (8).

In the following lemma, we demonstrate a lower bound for α_k under the initial Wolfe line search.

Lemma: Suppose the sequence of search direction $\{d_k\}$ and $\{F_k\}$ be determined by algorithm 4.1 Lemma: Assume that algorithm (MO4) determines the search direction sequence $\{d_k\}$ and $\{F_k\}$. This suggests that

Proof: By the given condition (8) we have

$$(\sigma - 1)F_k^T d_k \leq (F_k - F_{k-1})^T d_k \leq \|F_k - F_{k-1}\| \|d_k\| \leq \alpha_k L \|d_k\|^2, \quad (12)$$

Then

$$\alpha_k \geq \frac{\|F_k\|^2}{L \|d_k\|^2}.$$

Where $\frac{1}{L} \geq \frac{(1-\sigma)}{L}$, the step 2 comes by Cauchy-Schwarz inequality and step 3 comes by Lipschitz continuous. Since d_k hold (8) and $\sigma < 1$, this implies (12) satisfy. The proof is complete.

To obtain the globally convergent conjugate gradient projection method, we used the Zoutendijk condition, which is first given [8] along with the Wolfe condition. The line search of the proposed algorithms now satisfies the Zoutendijk condition, as the following lemma shows.

Lemma: The step length α_k is determined by the original Wolfe line search if assumption (B) is satisfied and the suggested method finds the search direction sequence $\{d_k\}$, $\{f_k\}$, then we obtain

$$\sum_{k=0}^{\infty} \frac{\|F_k\|^4}{\|d_k\|^2} < +\infty. \quad (13)$$

Proof: From (8) for any k that

$$f(x_k) - f(x_{k+1}) \geq -\rho \alpha_k F_k^T d_k \geq \rho \alpha_k \|F\|^2 \geq \frac{\rho(1-\sigma)\|F_k\|^4}{L\|d_k\|^2}$$

which the second and third inequality comes by (8) and (13). Therefore, by Assumptions (B)(i) that we get (13). The proof is complete.

As a result, we know that the iteration of (CGM) may fail, which means that only if $d_k \rightarrow \infty$ sufficiently quickly will $F_k \geq \mu$, $\sum k \geq 0$. An alternative interpretation is that the sequence $\{F_k\}$ can only be bounded away from zero if $k=0 \rightarrow \infty$. The global convergence of the proposed approach is now examined in the subsequent lemma.

Theorem: Suppose the sequence $\{F_k\}$ and $\{d_k\}$ be generated by the suggested method, we have

$$\liminf_{k \rightarrow \infty} \|F_k\| = 0 \quad (14)$$

Proof: Assume that (14) does not satisfy, let a constant $M > 0$ s.t.

$$\|F_k\| \geq M, \forall k \geq 0. \quad (15)$$

From (6), (7) and (8) we have

$$\|d_k\| \leq \|F_k\| + |\beta_k^{MO4}| \|y_{k-1}\| |\xi_k| \|d_{k-1}\|$$

$$\|d_k\| \leq \|F_k\| + \frac{\|y_{k-1}\| \|d_{k-1}\|^2}{\|d_{k-1}\| \|s_k\| \|y_{k-1}\| + \|d_{k-1}\| \|y_{k-1}\|}$$

$$\left(\frac{\|d_{k-1}\| \|s_k\| \|y_{k-1}\|}{\|y_{k-1}\| \|d_{k-1}\|^2} + \frac{\|d_{k-1}\| \|y_{k-1}\|}{\|y_{k-1}\| \|d_{k-1}\|^2} \right)$$

$$\leq \|F_k\| + \frac{\|y_{k-1}\| \|d_{k-1}\|^2}{\|d_{k-1}\| \|s_k\| \|y_{k-1}\| + \|d_{k-1}\| \|y_{k-1}\|}$$

$$\left(\frac{\|d_{k-1}\| \|s_k\| \|y_{k-1}\| + \|d_{k-1}\| \|y_{k-1}\|}{\|y_{k-1}\| \|d_{k-1}\|^2} \right)$$

$$\leq \|F_k\| + 1 \leq U + 1 \triangleq \theta,$$

Cauchy-Schwarz inequality, (8), (9), and trigonometric inequality, respectively, are the sources of the second, third,

and fourth inequalities. The last inequality comes by (11), (15) and Assumption (B)(i).

In synopsis, the sequence $\{d_k\}$ determined by our algorithm has a common upper bound such that.

$$\|d_k\| \leq \varsigma, \forall k \geq 0. \quad (16)$$

Additionally, $\varsigma = \theta$. By applying (15) and (16), it is demonstrated that

$$\sum_{k=0}^{\infty} \frac{\|F_k\|^4}{\|d_k\|^2} \geq \sum_{k=0}^{\infty} \frac{M^4}{\varsigma^2} = +\infty. \quad (17)$$

This implies a contradiction (16), thus conclude that (17) holds. The proof is complete.

Numerical Experiments

In this part, we give some insight into the conduct of our method. Some problems have been used to test and analyze the efficiency of a new method compared to some two-terms conjugate gradient method (NTT) [9], a three terms conjugate gradient method (NS) [10] and a conjugate gradient-like method (CGL) [11]. For everyone the test problems seven or eight initial point starting are used. Similar in [12], we check the test problem when the variables number $n=5000, 10000, \dots$ and some given starting points

$$x_0 = (10, 10, \dots, 10)^T, x_1 = (-10, -10, \dots, -10)^T,$$

$$x_2 = (1, 1, \dots, 1)^T, x_3 = (-1, -1, \dots, -1)^T$$

$$x_4 = \left(1, \frac{1}{2}, \frac{2}{3}, \dots, \frac{1}{n}\right)^T, x_5 = (0.1, 0.1, \dots, 0.1)^T,$$

$$x_6 = \left(\frac{1}{n}, \frac{2}{n}, \dots, 1\right)^T, x_7 = \left(1 - \frac{1}{n}, 1 - \frac{2}{n}, \dots, 0\right)^T.$$

All runs are proposed using MATLAB R2016a and run PC with 16GH, CPU2.30- Windows11 operation system. Numerical results are compared dependent on the number of iterations, the number of evaluation functions and CPU time. The terminating executions we used some criterion whenever $\|F_k\| \leq 10^{-6}$ and the total number of iteration exceeds 500000. The parameter of the new algorithm were set as follows: $\tau = 10^{-4}$, $\sigma = 0.5$ and $\gamma = 0.1$. The parameter of the other methods comes from [8, 13, 14]. The step-size α_k is computed by $\alpha_k = \max\{\alpha_{k-1}\gamma^i, i = 1, 2, 3, \dots\}$, which holds Wolfe line search condition. The table (1) indicate the number of iteration (N_i) and a number of function evaluations (N_f) while the table (2) indicate to CPU time (CPU). From these tables shows that the new method is promised.

Table 1: Numerical results of N_i and N_f .

Pt	Dim.	x_t	The new (MOD)		SCG		PRP	
			N_f	N_i	N_f	N_i	N_f	N_i
P1	10000	x_0	272	60	30004	10001	30004	10001
	10000	x_1	485	56	30004	10001	30004	10001
	10000	x_2	238	52	30004	10001	30004	10001
	10000	x_3	459	49	30004	10001	30004	10001
	10000	x_4	903	159	30004	10001	30004	10001
	10000	x_5	92	18	30004	10001	30004	10001
	10000	x_6	297	53	30004	10001	30004	10001
	10000	x_7	297	53	30004	10001	30004	10001
P2	1000	x_0	174	36	49	16	2113	704

	1000	x_1	211	27	49	16	3004	1001
	1000	x_2	103	21	52	17	3004	1001
	1000	x_3	411	36	52	17	2080	693
	1000	x_4	7876	1201	3004	1001	3004	1001
	1000	x_5	87	15	3004	1001	1981	660
	1000	x_6	6209	316	3004	1001	3004	1001
	1000	x_7	6088	303	3004	1001	3004	1001
P3	10000	x_0	363	42	979	326	30004	10001
	10000	x_1	8815	521	49	16	2062	687
	10000	x_2	196	25	400	133	1993	664
	10000	x_3	4625	2807	1024	341	30004	10001
	10000	x_4	7438	465	30004	10001	30004	10001
	10000	x_5	8504	5000	30004	10001	2017	672
	10000	x_6	153	24	30004	10001	30004	10001
P4	10000	x_7	1240	125	30004	10001	30004	10001
	10000	x_0	4781	5000	30004	10001	30004	10001
	10000	x_1	4781	5000	30004	10001	30004	10001
	10000	x_2	4781	5000	30004	10001	30004	10001
	10000	x_3	4781	5000	30004	10001	30004	10001
	10000	x_4	4781	5000	30004	10001	30004	10001
	10000	x_5	4781	5000	30004	10001	30004	10001
P5	10000	x_6	4781	5000	30004	10001	30004	10001
	10000	x_7	4781	5000 500	30004	10001	30004	10001
	5000	x_0	75	13	15004	5001	15004	5001
	5000	x_1	336	28	15004	5001	15004	5001
	5000	x_2	352	25	15004	5001	15004	5001
	5000	x_3	1155	75	15004	5001	15004	5001
	5000	x_4	1123	80	15004	5001	15004	5001
P6	5000	x_5	257	19	15004	5001	15004	5001
	5000	x_6	550	40	15004	5001	15004	5001
	5000	x_7	470	36	15004	5001	15004	5001

Table 1: Continued

P6	50000	x_0	100996	6497	150004	50001	150004	50001
	50000	x_1	3110	169	150004	50001	150004	50001
	50000	x_2	128953	7868	150004	50001	150004	50001
	50000	x_3	335069	26445	150004	50001	150004	50001
	50000	x_4	427153	22647	150004	50001	150004	50001
	50000	x_5	313149	18091	150004	50001	150004	50001
	50000	x_6	55455	2645	150004	50001	150004	50001
P7	50000	x_7	113570	6887	150004	50001	150004	50001
	500000	x_0	182	66	34	11	2833	944
	500000	x_1	536	47	34	11	1237	412
	500000	x_2	179	63	34	11	1513	504
	500000	x_3	472	50	34	11	150000	500001
	500000	x_4	40532	6507	34	11	2095	698
	500000	x_5	15	3	34	11	1318	439
P8	500000	x_6	185	63	34	11	2518	839
	500000	x_7	185	63	34	11	1606	535

Table 2: Numerical results of CPU-time.

Pt	Dim.	x_t	CPU-time		
			The new (MOD)	SCG	PRP
P1	10000	x_0	2.046875	285.3437	3.6718
	10000	x_1	3.31250	297.0468	2.6562
	10000	x_2	1.8750	295.0625	1.5625
	10000	x_3	2.98437	298.8281	3.7343
	10000	x_4	6.85937	299.4531	1.8750
	10000	x_5	0.62500	304.8906	1.9218
	10000	x_6	2.48437	300.2187	1.8437
P2	10000	x_7	2.56250	312.6875	1.7656
	1000	x_0	1.73437500	2.0156	0.9531
	1000	x_1	1.46875000	1.8906	1.7187
	1000	x_2	0.90625000	2.1718	1.4062
	1000	x_3	2.56250000	1.6562	0.9375
	1000	x_4	57.6406250	112.9062	1.2500
P3	1000	x_5	0.57812500	115.6093	1.0937

P3	1000	x_6	38.0156250	117.5000	1.4062
	1000	x_7	42.500	119.8906	1.5625
	10000	x_0	0.37500	36.70312	9.2031
	10000	x_1	958.640625	1.9687	0.5000
	10000	x_2	0.25000	15.3593	0.6250
	10000	x_3	676.843750	38.2031	8.5937

Table 2: Continued

P3	10000	x_4	121.015625	1144.7500	8.1250
	10000	x_5	7475.48437	1144.5625	0.9531
	10000	x_6	0.12500	1167.8125	14.062
	10000	x_7	0.59375000	1167.9218	15
P4	10000	x_0	147.68750	317.2343	0.2968
	10000	x_1	126.70312	334.7031	0.1406
	10000	x_2	119.14062	337.8437	0.1406
	10000	x_3	120.81250	337.3593	0.1875
	10000	x_4	146.14062	339.1562	0.1562
	10000	x_5	1715.59375	339.6250	0.1406
	10000	x_6	223.82812	337.9687	0.1250
	10000	x_7	220.21875	338.8593	0.1562
P5	5000	x_0	1.10937500	565.3593	0.2500
	5000	x_1	3.5000	580.0156	0.0937
	5000	x_2	3.593750	576.3750	0.0937
	5000	x_3	12.1093750	578.9531	0.0937
	5000	x_4	11.5156250	576.9531	0.0937
	5000	x_5	2.67187500	566.3906	0.0781
	5000	x_6	6.03125000	567.7343	0.1250
	5000	x_7	5.32812500	584.8906	0.0781

Table 2: continued

P6	50000	x_0	263.625000	1628.3437	15.0781
	50000	x_1	7.95312500	1696.1875	15.7812
	50000	x_2	307.968750	1695.0625	32.7500
	50000	x_3	778.234375	1704.0312	31.3906
	50000	x_4	981.281250	1687.4375	32.0625
	50000	x_5	716.390625	1698.5468	30.0625
	50000	x_6	128.203125	1670.0468	34.0156
P7	50000	x_7	267.187500	1674.4375	35.6406
	500000	x_0	2.21875000	35.6093	0.4531
	500000	x_1	3.28125000	35.2343	0.1250
	500000	x_2	1.39062500	34.4687	0.1250
	500000	x_3	2.54687500	35.1406	79.3437
	500000	x_4	246.578125	34.3437	0.0937
	500000	x_5	0.062500	36.3593	0.0937
	500000	x_6	1.56250000	36.2812	0.0937
	500000	x_7	1.5000	36.1562	0.1250

forementioned tables show that our algorithm outperformed the other algorithms in most cases..The following terms were compared, it should be mentioned::

* The a

The number of repetitions.

* How many function evaluations there are.

CPU duration.

Conclusions

The (MOD) method under Wolfe condition is a novel approach to solving unconstrained optimization problems using the conjugate gradient (CG) algorithm. This method works well for large data sets because of its limited storage capacity. The global convergence has been proven for the proposed algorithm. Our approach has a competitive advantage over the other three conjugate gradient methods, and numerical results showed that it is a promising and practical tool for solving optimization problems.

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MATLAB أسلوب خوارزمي متقدم للتحسين باستخدام برمجة

المستخلص

لحل مسائل (CG) تقدم هذه الورقة البحثية خوارزمية جديدة للتدرج المترافق (في ظل شرط وولف. تتمثل الحجة (MOD) التحسين غير المقيدة: طريقة) على تقليل حساب الدوال، ووقت وحدة (MOD) الرئيسية في قدرة طريقة (الإصدار) MATLAB المعالجة المركزية، وعدد التكرارات. يستخدم برنامج SCG ومقارنة النتائج العددية مع طريقتين شائعتين، هما طريقة (R2016a) لتوضيح ذلك. عند اقتراح بحث خطي مناسب واستيفاء الشروط، PRP وطريقة المطلوبة، تتمتع الطريقة المقترحة بخاصية الانحدار الكافي. نُقدم في هذه الورقة كلاً من التقارب العالمي والخوارزمية المحددة جيداً. تظهر هذه النتائج أن الاستراتيجية الجديدة تتفوق على الخوارزميات التقليدية.